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De Liu

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The Optimal Design of Skill-based Consumer Contests in the Context of Online Entertainment

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The Optimal Design of Skill-based Consumer Contests in the Context of Online Entertainment

by

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To My Parents

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The Optimal Design of Skill-based Consumer Contests in the Context of Online Entertainment

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Supervisor: Andrew B. Whinston

This dissertation looks at several issues in designing an optimal skill-based consumer contest (SBCC). Consumer product (or service) companies, such as online entertainment providers, often use SBCCs to promote the consumption of their products (or services). The main objective of a SBCC is to maximize the profit from the enhanced consumption by consumers rather than their outcome in the contest. This research is the first to investigate design issues in contests of this kind.

The first part of the dissertation explores the role of SBCCs in online entertainment area by focusing on the status-seeking behavior of human beings. Drawing from psychology literature, I argue that the desire for status provides a

strong motive for consumers to compete with each other in online entertainment communities.

In the second part of the dissertation, I build a game-theoretical modelto study a handful of design issues arising from the SBCCs. In this framework, a monopoly firm faces *n* consumers who may differ in skill levels. The firm offers a set of prizes to consumers in a SBCC that requires two inputs: skill and consumption. One of the main findings in this research is that a Winner-Take-All prize structure is often optimal (but not always) for the SBCCs. Another finding is that consumers will compete more aggressively when their skill levels are closer to each other. As a result, the firm may be better off by segmenting consumers based on their skill levels. In addition, in some cases, the firm is better off by charging an entry fee to exclude low-skilled consumers. These findings contribute to existing literature on contest designs and provide practical guidelines for structuring a SBCC.

The last part of the dissertation empirically analyzes two individual-level datasets from a wireless game to verify the insights obtained from the theoretical model.

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Introduction

In last few years, the focus of the entertainment industry is shifting away from delivering products and services to nurturing users' experience within a network of online communities. In this new networked computing environment, active participation of users and interactions among them become critical part of the experience-creation process. This dissertation explores how companies can take advantage of this technology-enabled community environment by organizing skill-based consumer contests (SBCCs) to increase the aggregate usage of online entertainment services.

This dissertation contains three essays arranged in chapter order. The first essay is based on my prior work on a book chapter titled "Status Seeking and the Design of Online Entertainment Communities". The book chapter is forthcoming in Karmarkar and Apte eds. (2004) "Managing in the Information Economy: Current Research Issues". In this essay we overview the recent development of the online entertainment industry and develop an understanding how SBCCs could enhance entertainment companies' profits. One implication is that like other social environments, users in online entertainment communities have a natural tendency of pursuing status among their peers. Another implication is that status-seeking activities, if properly aligned with entertainment companies' objective, can increase the aggregate usage of online entertainment services and therefore enhance the companies' profitability.

The second essay is based on a research paper being revised for Marketing Science. This essay develops insights on how to optimally structure SBCCs in online entertainment communities. We model status seeking as a SBCC played by n users. A user's performance in SBCCs is jointly determined by her inherent skill and the level of usage she chooses. The company chooses the prize structure and the contest structure to maximize the aggregate usage of all users. One of the main findings is that the optimal prize structure is either Winner-Take-All or Split-Prize (i.e. equally splitting the prize sum among first j winners). Winner-Take-All is often optimal, especially when the number of users is large. A second finding is that the company is worse off by segmenting users based on non-skill factors such as geographical regions. However, it may be better off by segmenting users based on their skill levels. We also show that the company is better off by running a SBCC that has higher marginal substitution of usage for skill. Finally, under some circumstances, the company should charge an entry fee to exclude low-skilled users. These results offer important theoretical guidance for the designers of SBCCs. This research is the first to study the design of contests with an objective of maximizing aggregate input of all participants.

The third essay employs empirical analysis to achieve two objectives: 1) to detect status-seeking behavior in online entertainment communities and 2) to test whether the displayed playing behavior is consistent with the equilibrium prediction. We have collected two datasets for a mobile game. We conduct a logit regression on the stop event (a stop event happens if the next game time is more than one hour later). We find that users displays a "stopping rule" behavior, i.e. the probability of stop increases after obtaining a high score, which indicates the possibility of status-seeking.

Chapter 1. Status Seeking and Its Implications for the Design of Online Entertainment Communities

1.1 Introduction

"*The online experience, the ability to create virtual communities online, is going to be a much bigger part of the industry going forward*."

-- Robbie Bach, Microsoft Xbox Chief Officer

The development of new information and communication technologies has initiated a radical transformation in the entertainment industry, characterized by the decline of passive entertainment and the rise of the interactive online entertainment. The traditional model of selling packaged content to customers met serious challenges from disruptive technologies. Amid the proliferation of the digital music and the peer-to-peer file sharing on the Internet, global music sales has dropped by 5% in 2001, then 7% in 2002 (BBC News 2003). The television industry is also suffering accelerating loss of audience, partially attributable to the digital video recorder technology, such as TiVo, which enables users to record shows and playback on their own time, often without commercials. According to a recent report (Nelson and Peers 2003), young adult viewers of prime-time television have dropped sharply by 7% last year.

The new interactive online entertainment, represented by electronic gaming has enjoyed high growth rates for the past decade despite the technology slump. The 2002 sales for game software, hardware and accessories increased by 8% to reach $10.3 billion, surpassing Hollywood record box-office sales of $9.27 billion (Black 2003). The top sports game title, Madden NFL 2004 by Electronic Arts, reaped $200 million in sales and attracted more eyeball hours than HBO's hit show The Sopranos.

Massively Multiplayer Online Games (MMOGs) is one new and fast-growing segment of online entertainment. MMOGs are originated from text-based multi-user dungeons (MUD) in late 70's. The first true MMOG, Ultima Online, was launched in 1997 and has since built a subscriber base of about 250,000 players. The global market for MMOGs is expected to reach $2.7 billion in revenue by 2006 (Staehlin 2003).

MMOGs usually allow thousands of players to inhabit and adventure in a virtual game world at the same time. A long-standing success in MMOG history in United States is EverQuest®. Each player in EverQuest starts by choosing a game character, called an avatar, from a handful of races. Avatars can have their own appearance, skills, professions, and social connections. Players can maneuver their avatars to perform a variety of activities, such as exploring lands, managing assets, taking on monsters or foes, and making friends. Since launched in 1999, EverQuest has amassed 500,000 subscribers. A major attraction of EverQuest and other MMOGs lies in the ability for players to live in an alternate reality – while the world and avatars only exist in bytes, players' experience are real.

Figure 1. An EverQuest Screenshot

Another expanding area of online entertainment is mobile gaming. Mobile games utilize wireless data technologies, such as SMS (short messages) or WAP, to enable real-time interaction between users and servers and among users. The idea of using wireless gaming to accelerating wireless data usage has gained a lot of attention among telecom companies. By 2002, mobile gaming had become the top wireless data traffic in Europe. The global mobile game industry is estimated to generate $12.8 billion in revenue by 2008 (Frost & Sullivan Report 2002).

Mobile Millionaire is an example of successful mobile games in early days. The game is based on the popular TV show “Who Wants to Be a Millionaire.” Players of Mobile Millionaire answer trivia questions stored on a game server. The game is designed such that players can retrieve and answer trivia questions using their mobile phone through the SMS, WAP, and etc. Users are billed according to the number of messages or actual number of data packets. In some cases, users also need to pay a premium fee for playing a game title. The following figure illustrates a SMS version of Mobile Millionaire game.

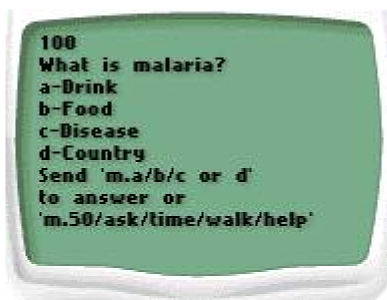

Figure 2. Mobile Millionaire

Simple in its design, Mobile Millionaire is played by millions of users around the world. Mobile Millionaire is more often played in a social context: a group of friends gather to start a race to high scores each on their own cell phones.

Both MMOGs and mobile games embrace the idea of interaction among a community of users. Such an idea also took off among the traditional console segment. In 2002, all the Big Three game console makers, i.e. Sony, Nintendo, and Microsoft, have supplemented their game consoles with Internet connections. This move was heartily welcomed by players: according to an analyst in GartnerG2, in just three months some 400,000 gamers have adapted their game consoles for playing online (Lewis 2003). Microsoft has recently launched the Xbox Sports Network, which allows Xbox users to connect to the Xbox Live service to take on each other in an virtual tournament. Microsoft contended that the creation of online communities instead of content will become the biggest part of the industry.

These trends reflect that the focus of the entertainment industry is shifting away from delivering products and services to nurturing user's online experience. In new online entertainment, the entertainment companies are no longer sole producers of entertainment value. Rather, in the words of Prahalad and Ramaswamy (2003) in their award winning article, "individual customers actively co-construct their own consumption experiences through personalized interaction, thereby co-creating unique value for themselves".

Given the crucial role of online communities in online entertainment, it is imperative to understand how entertainment companies can use online communities to nurture users' experiences. In this dissertation, we focus on the status seeking behavior and its implications for the design of online entertainment communities.

1.2 Status Seeking in Online Entertainment Communities

Status and the pursuit of it is one of the main themes in online entertainment communities. For example, an avatar in EverQuest with 50+ levels is considered as a celebrity in the virtual world. Players often show off their status through their equipment and their levels of achievement. Mobile Millionaire features a monthly hall of fame to recognize best-performed players of the month. Sometimes it also gives cash prizes and/or cell phones to the winners. The following figure shows an example of a hall of fame used by Virgin Mobile Telecom.

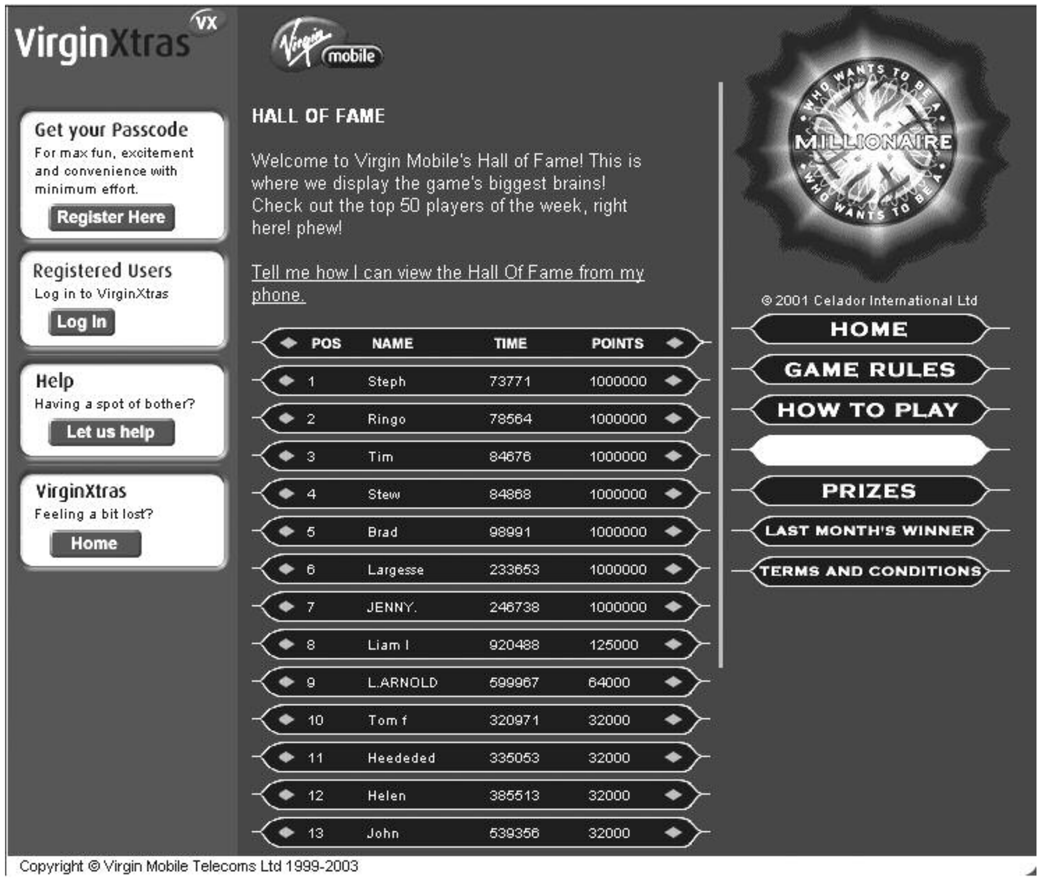

Figure 3. The hall of fame for Mobile Millionaire

In this dissertation, we try to explore the role of status seeking in online entertainment communities and to study how companies can influence status seeking to increase the aggregate usage of online entertainment service.

This research is important for three reasons. First, the value of status is an important value provided by online entertainment communities. From gamers craving for halls of fame to racing to higher levels in MMOGs, it is impressive how concerned people are with their status in online entertainment communities.

Second, this research is particularly important because of the unparalleled opportunities for entertainment companies to influence status seeking. In online entertainment communities, not only providers can choose what status criteria to use and what the status symbols look like but also they can decide on what are legitimate status-seeking activities and who will compete with whom. Many online entertainment providers have introduced halls of fame, rankings, tournaments and ladders to induce status seeking. However, there are few theoretical guidelines on what is the most effective design of these instruments.

Finally, the advantages of doing research in this area lie in the uniqueness of online entertainment industry as a source of data on user behavior and as a field for experimenting on different designs. Due to the digitalized nature of online entertainment communities, it is often easier to collect information on user behavior and manipulate design features.

1.3 Why Do Users Seek Status In Online Entertainment Communities?

In sociology literature, status refers to one's *relative* standing in a social hierarchy as determined by respect, deference and social influence (Ridgeway and Walker 1995). The desire of status is one of the basic needs of human being (Moslow 1968, 1971). Csikszentmihalyi (2000) wrote that the need for status and self-esteem in general, "is presumably active even when the lower-order needs are not entirely met" and "becomes fully active after survival, safety, and belongingness needs are more or less taken care of." Studies by sociologists showed that status seeking is pervasive in virtually all societies (Ball et al. 2001).

Many researchers in sociology view status as a means to obtain resources (Lin 1990, 1994) or power (Thye 2000). Thus, status is pursued as a "rational" tool. In line with this view, Ball and his colleagues found in experimental settings that individuals with higher status were conceded higher benefits in negotiations (Ball and Eckel 1996) and markets exchange (Ball et al. 2001). This view is consistent with the fact that many social and economic resources, such as tenure positions and salesperson's compensation, are allocated based on relative rankings.

Another view holds that status is not only a means to an end but also an (emotional) end in itself. Evolutionary anthropologists have identified status seeking as an ancient emotional tendency in primates (Barkow 1975). Biological experiments on monkeys connected the gaining of status to high blood serotonin levels (blood serotonin level is associated with pleasure) (McGuire & Raleigh 1985). Therefore, people may pursue status for emotional reasons rather than external benefits. In a recent study, Loch et al. (2003) showed that people valued status even when status was nothing but applause from audience. Indeed, in online gaming examples, people show interests in pursuing a hall of fame or rankings, even without prizes or other immediate extrinsic rewards.

In online entertainment communities, both views may be plausible. On the one hand, status in online entertainment communities is often a symbol of competence. Therefore, users may pursue it as an emotional end in itself. On the other hand, status in online entertainment communities may also lead to physical resources (such as prizes in Mobile Millionaire) or virtual resources (such as a privilege to enter a special game zone)[1].

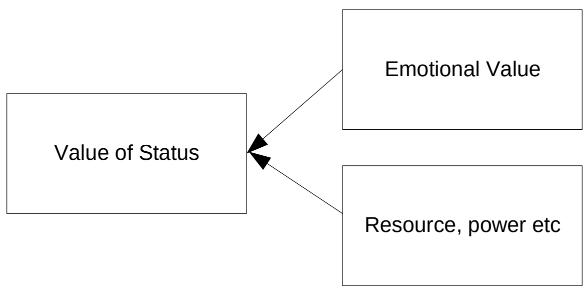

Figure 4. the value of status

1.4 The Business Value of Status Seeking

The value of status seeking in online entertainment communities lies in its incentive power: the desire for status can motivate users to take actions to gain status, which may induce a higher level of usage. We call these status-building actions as *status-seeking activities*. Status-seeking activities can overlap with the

[1] It is also worth noting, that some game players sell their avatars in EverQuest through EBay (although Sony banned this). In such a case, a user may pursue a status for its trade value.

normal usage activities. For instance, in Mobile Millionaire some users are willing to play more games just for entering the hall of fame. To mobile network operators, it means more revenue from such users.

Status seeking activities may become a regenerative source of revenue. Whenever other users raise their bid for status, one has to keep up by putting in more effort to maintain her status. In contrast, entertainment content will never regenerate its value once exhausted. When entertainment content is very costly to produce, status seeking can be an invaluable to online entertainment companies. Status seeking may explain why MMOGs have much longer life span (EverQuest has been around for almost 5 years) than their PC counterparts (many exist for no longer than a year). Some players surprised themselves when they came back to the same MMOG after a half year and saw almost a whole new world.

Status-seeking activities can also be intrinsically valuable to users. Just as playing a Mobile Millionaire can be fun while it is status-building. Csikszentmihalyi (1975) show that the use of skills itself can be a source of enjoyment. In this case, status-building has to be a part of what an online entertainment service has to offer.

Of course, status seeking activities may bear some costs to users. By pursuing status, users have to spend time, effort, and/or monetary payment (e.g. the data packet fee one has to pay in Mobile Millionaire case). How much a users is willing to pursue status depends on the tradeoff between the intrinsic fun of status seeking activities and the cost of it, on the worth of status, and on individual traits (such as whether the user is an achiever-type or an explorer-type).

In summary, users' value from status seeking activities comes from the value of status and from their intrinsic value toward status seeking activities. The amount of status seeking activities should increase in the users' valuation for status and in users' intrinsic value towards status seeking activities. The amount of status seeking activities should decrease in the cost of conducting such activities.

The company can potentially capture users' value in status seeking activities, such as through usage fee, although it may not always be able to do so. For instance, one of the controversial issues in massively multiplayer online gaming is macroing, i.e. using macros to simulate keyboard and mouse movements so that one can collect game credits without playing in person. While macroing enhances one's status (assuming macroing can not be detected or punished), it reduces the player's lifetime with the game and so eventually undermines the online entertainment provider's profits.

Figure 2 summarizes the relationship between status, status seeking activities, user value, and company profits.

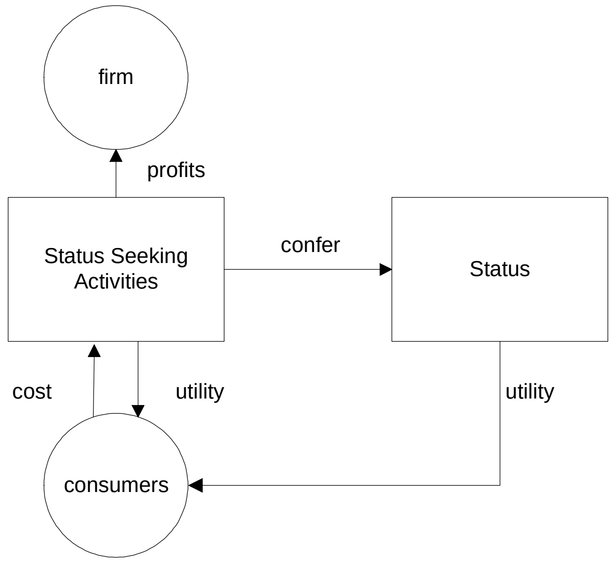

Figure 5. The value of status seeking in online entertainment communities

The notion of status-seeking activities is similar to that of “positional goods” due to economist Robert Frank (1985). Houses and cars are positional goods because they not only generate consumption utility but also a positional utility, i.e. demonstrating one’s status. Frank showed that when people are concerned about relative positions, they tended to over-spend on positional goods. By this argument, when users are concerned about their status in online entertainment communities, they also tend to spend more on entertainment.

1.5 A Game-Theoretic Framework for Studying Status Seeking

Status seeking in online entertainment communities is analogous to the race by the business schools to get a good ranking, except that prizes for business school rankings are high-quality students (Schatz 1993) and the prizes for high-ranking in online games are more of psychological rewards. Status seeking falls into the generalized notion of *contests* in economics literature, which encompasses various economic and social activities such as rent seeking, patent racing, R&D tournaments, salesperson competition, and so on. A common element of these different activities is that the allocation of the resources – monopoly rents, patent, prizes, funding and student quality – are based on the relative performance of participating parties. To put it in economic terms, "contests are situations where agents spend resources to compete for one or more prizes" (Moldovanu and Sela 2001).

We also adopt a game-theoretic approach to study status-seeking contests. A status-seeking contest is viewed as a game played by individual users, where usage is their investment and the status is their prize. Game-theoretic approach is widely adopted in economic literature in studying contests. For instance, in the seminal work by Lazear and Rosen (1981), contests are formulated as a competition among agents each of whom invest unobservable amount of effort to produce an output valued by a principal. The game-theoretic approach enables us to obtain theoretical insights on how design variables, such as prize allocation and the segmentation of the population, can affect the profits of online entertainment providers.

We start with a somewhat general framework that accommodates different specifications of status seeking contests. We present its use in next section with further specifications on model assumptions. It is useful to start with describing the key variables captured in the generalized model.

- **Usage** We assume the main status -seeking activity in online entertainment communities is using the service provided by the online entertainment provider, denoted by the variable *usage* (measured in hours). Usage plays three roles in our context. First of all, the usage of the service provides intrinsic value of entertainment to users. Second, it costs users money in the form of payment made to the online entertainment providers. Third and importantly, usage (and ability) improves one's performance therefore helps one to gain status.

- **Ability**. Ability reflects users' talent or skills. In our framework, one's performance is not only affected by usage levels but also by her ability. Heterogeneity in user ability levels is virtually inevitable in online entertainment communities. Such heterogeneity may arise either because users are different in their talents per se (e.g. the eye-hand coordination skill or the acccurary of recall) or because they have gained different levels of experience. Because most status-seeking contests in online communities are skill-based, we preserve the ability factor as an important variable in our framework. Note that skill-based contests are different from games of luck, such as lotteries or sweepstakes. In the latter case, only the number of entries (corresponding to usage) affects one's chance of winning.

Following conventions in the economic literature, we assume that ability is *private information*, i.e. each user knows her own ability[2], but does not know others'. This assumption is consistent with the fact that in online communities it is more difficult to assess others' true ability, given that individuals can so easily hide behind their IDs or avatars. We assume ability factors are drawn from a common distribution, referred to as the *ability distribution*, and this distribution is *common knowledge* to all the users and the online entertainment provider. In reality, users may gain such knowledge from their previous observations or indirectly from their peers. Note that the ability distribution is ex ante knowledge and the realized ability profiles of the population are not known to the user.

● **Random factor**. Sometimes to win a status seeking game, one needs not only usage and ability but also a bit of "luck". We model such luck as the random factor in a user's performance. Note that the magnitude of the randomness can

[2] However, the assumption that users know their own ability may be questionable because some studies suggest individuals may misjudge their own abilities or lack of knowledge about themselves (Tversky and Kahneman 1974). More research is needed to account for these considerations.

sometimes be controlled by the designers of online communities, e.g. by introducing randomness in the outcome of a fight with monsters.

We consider there are n *potential* users of the online entertainment service, indexed by $i = 1...n$. A user's *performance* (x_i) is affected by her *usage* (t_i), *ability* (μ_i), and a random factor (ε_i). We let the performance function be $f(t_i, \mu_i, \varepsilon_i)$. f increases in all three arguments. We assume each ability parameter is an independent draw from a common distribution F and each random factor in performance is an independent draw from a common distribution G. We assume that F, G and n are known by all the users and the online entertainment provider (note that actually number of participating users may be less than n).

Status is allocated according to rank-order performance of participating users. We also call status as a *prize* due to their common nature. All users agree upon the value of status. Denote the value of ranking the first as v_1, the value of ranking the second as v_2, and so on ($v_1 \geq v_2 \geq ... \geq v_n$). We denote the status vector as $\boldsymbol{v} = [v_1, v_2, ...v_n]$.

A user's overall utility consists of the utility from winning a status, the intrinsic utility of using the online entertainment service, and the disutility of payment to the online entertainment provider. Let $\boldsymbol{\rho}_i = [\rho_{i1}, \rho_{i2}, ...\rho_{in}]$ denote the user *i*'s probability of being *jth* in the contest, given her ability μ_i and her usage t_i.

Her expected utility from status is $\sum_{j=1}^{n} \rho_{ij} v_j$. We assume her intrinsic utility from usage is $\theta_i \cdot t_i$ and her payment to the online entertainment provider is $p \cdot t_i$. The overall user utility is given by,

$$U_i(t_i, \boldsymbol{\rho}_i) = \sum_{j=1}^{n} \rho_{ij} v_j - pt_i + \theta_i t_i$$

Note that not only $\boldsymbol{\rho_i}$ is affected by x_i (hence t_i, μ_i and ε_i) it is also affected by $x_j(j \neq i)$ (hence μ_j, t_j, and ε_j). But since a user does not know others' ability parameters or their choice of usage level, she can form an estimation of others' performance based on her knowledge about common distribution F and G as well as her belief about others strategy discussed below.

A user's *strategy* is defined as a mapping from her ability parameter to her choice of usage level, denoted as $t_i(\mu_i)$. A strategy profile of all users forms a *Nash equilibrium* if it satisfies an *incentive compatibility* (IC) condition, which requires that she does not want to deviate from her strategy given other users' strategy, and an *individual rationality* (IR) condition, which requires that her expected utility of participating in the contest is non-negative.

We assume the marginal cost of providing online entertainment service is a constant, which we can normalize to zero without loss of generality. In addition, the online entertainment provider also incurs a fixed fee for organizing the contest denoted as K. K may include the cost for prizes, hiring judges, advertising fee, etc. Since K is sunk cost, we can drop K from consideration in the provider's profit function without affecting the study of the design issues.

We assume online entertainment charges a fixed subscription fee p_e and a usage fee p for using online entertainment service. When $p_e = 0$, the online entertainment provider purely replies upon usage fee for profits. When $p = 0$, the online entertainment provider only charges a subscription fee and usage is free of charge. In the former case, the online entertainment provider maximizes the aggregate usage of all users. In the latter case, the online entertainment provider maximizes the number of users who participate in online entertainment communities. An intermediate case is that the online entertainment provider charges a subscription fee plus a certain usage fee. All three cases are seen in real world applications.

The expected profit of the online entertainment provider therefore writes,

$$E\left[\sum_{i=1}^{n}\left(p_e\delta_i + pt_i\right)\right], \text{ where } \delta_i = \begin{cases} 1, \text{if } i \text{ participates} \\ 0, \text{if else} \end{cases}$$

Note that at the time of designing the online entertainment community, the online entertainment provider does not know the exact ability parameters of users. As a result, δ_i and t_i, which depends on μ_i, can be treated as random variables from the online entertainment provider's point of view.

This framework captures the main feature of status seeking in online entertainment communities. First, it reflects that the usage of an online entertainment service not only generates the value of entertainment, but also gives rise to the value of status. Second, it captures the fact that users differ in ability, which can explain the variation in the level of status-seeking activities. Third and importantly, the design objective of the online entertainment communities is to maximize the total “input” of all users rather than their “outcome”.

1.6 Implications of status seeking for the design of online entertainment communities

Although striving for status is “built into us”, the value of status and the rules of status seeking to some extent are selectable by the companies (Barkow 1989). The possibility of shaping status seeking is the most important premise for this research. Such a possibility is higher in online communities than in off-line communities because companies who organize online communities can manipulate them more easily. In general, design issues associated with status seeking may include the following.

Manipulating the value of status. Although different users may valuate status differently, the companies still have plenty of room to manipulate the value of status. According to our previous discussion, companies can enhance the value of status by increasing the emotional value attached to the status (e.g. giving special recognition) or by increasing the resource associated with status (e.g. giving monetary prizes, in-game credits, or privileges). Were prizes given, companies need to decide on the number and size of prizes. Even if no prizes given, companies need to consider the number of users who will receive status recognition.

Rules for status seeking. Although users may decide for themselves what is worth seeking and how to seek, companies can certainly influence what is considered as encouraged status and status-seeking behavior in online entertainment communities. This could be done by accounting for users' performance one way or another and by allowing or banning certain kinds of activities. Particularly in online gaming, a level system is crucial part of rules for status seeking. The company can also choose the information transparency in online entertainment communities: to what extent a user should know about her peers' skill levels? Finally, the company can also influence the uncertainty in users' performance. For example, the company can adjust the game parameters to make the probability of winning a battle with a monster depend more on luck.

Managing the population. Should the company segment users into groups or levels? How does the company decide on the size of each group? Should the company allow users to participate in a certain status-seeking challenge? These design issues can potentially affect the health of an online entertainment community.

Of course, the above list is much longer than we can possibly address in this dissertation. In chapter two, we will examine some of the important design issues in a specific framework, including the prize structure, segmentation, choice of performance measures and entry fee.

We have chosen to examine the above design issues using a skill-based contest model. Because status is awarded on a relative base, the game of status seeking falls into the notion of *contests* in economics literature, which encompasses rent seeking, patent racing, R&D tournaments, salesperson competition and so on. A common element of these different contests is that the allocation of "prizes" is based on the relative performance of participating parties. To put it in economic terms, "contests are situations where agents spend resources to compete for one or more prizes" (Moldovanu and Sela 2001).

The game-theoretic approach enables us to characterize users' choice of the level of status seeking activities. On top of that, we are able to analyze how the design variables, such as prize allocation and the segmentation of the population, can affect the profits of online entertainment providers.

1.7 Beyond Online Entertainment Communities

Status seeking is not exclusive to online entertainment communities. In fact, status seeking virtually exists in all online communities. Here are a few examples.

● **Peer-to-peer customer support communities**. A rationale behind peer-to-peer support is that customers can be effective contributors of knowledge in online communities, provided with appropriate incentives. Peer- and self-supports redirect part of the huge burden of customer support to customers themselves and are therefore expected to save costs. Rewards and token recognitions based on certain rankings are among the commonly used strategies by community providers (Gu and Sirkka 2003). For example, Hewlett Packard (HP) operates 35 discussion boards for novices and (internal or external) experts to share their knowledge, information and to encourage learning. The following figure shows HP ranks members by the number of answers posted and uses the "hall of fame" to recognize frequent contributors.

Top Community Enthusiasts: view all | become an enthusiast!

Answers*	Username
12554	topdog
6635	mlcohen
3270	msb113
2776	JSntgRvr
2226	fireberd
1370	moondog69
994	kltsin1
808	LarryA
702	AMDWOLFMAN
675	licher

topdog

* Indicates answers in all categories.

Figure 6. The rankings of contributors in HP's customer community.

● **Customer-supplied reviews.** Customer reviews are crucial for online retailers such as Amazon.com. It provides important third-party information on quality about products and services and thus increases buyers' confidence in making purchase decisions. Given the voluntary and neutral-grounded nature of customer reviewers, monetary incentives are inappropriate for such a setting. Non-monetary recognitions serve as an exclusive tool for rewarding customers. Anecdotal stories on newspapers suggested that a little token saying "top-500 reviewers" or "top-100 reviewers" provide a powerful (emotional) status reward to those volunteer customer reviewers. The following picture illustrates the recognitions of top-ranked customer reviewers at Amazon.com.

Figure 7. Amazon's top reviewers

One thing remains common among these examples: status becomes meaningful to users when it conveys signals about one's skill. What is likely different in above-mention online communities is the way status seeking activities tied to the company's objectives. In online entertainment communities, the company only cares about usage (*input*); a user's performance (*output*) is valueless to the company. However, in consumer reviewer communities or peer-to-peer support communities, the company may care as much the quantity of user postings (input) as the quality of them (output). In addition, the nature of interaction among users in above two examples is also different from that of online entertainment communities.

Despite these differences, the notion of status seeking as well as the game-theoretic framework we are going to study are applicable to these online communities as well. Results we obtain in the following chapter may be applied to these online communities with some modifications.

To conclude, we identify status seeking to play a role in online entertainment communities. Status seeking as potential driver for usage provides value to online entertainment companies. We discuss the opportunities for the company to influence status seeking, which give rise to the importance of the research in the next chapter.

Chapter 2. The Optimal Design of Skill-Based Consumer Contests

2.1 Research Questions and Motivation

In this chapter we study the optimal design of a SBCC. Three major characteristics of a SBCC make the study of it unique in the sales promotion literature. First, unlike price-cut or coupon-based sales promotion that rewards a consumer based on her absolute usage level, a SBCC considers her relative performance with respect to other users. Second, in a SBCC users are differentiated by skill levels, thus a company is often concerned about how users' usage pattern is affected by their level of skill. Third and most strikingly, while prior research on various types of contests focuses on optimizing some measure of *output*, such as the total sales volume of all dealers in a salesperson contest, in a SBCC the company tries to maximize the total *input* to the contest – namely the total usage by all users.

In this chapter we study the following two sets of questions, all centering around the objective of maximizing total usage of the service. The first set of questions is on prize structure, including how many prizes should be offered, and how the total award should be allocated among all prizes. The second set is on contest structure, including whether and how to segment the user population, how to set the admission policy, and whether to handicap high-skilled users. The relevance of these questions to business practice is evident from the fact that, with a scarce of theoretical guidance, many businesses are now actively experimenting with various prize and contest structures. For example, Mobile Millionaire offers one grand prize of $26,260 in one country and 10 prizes in another country, ranging from $1,138 to $23. Our personal interactions with industry professionals also reveal that experimenting is usually slow, costly, and often do not generate enough knowledge for improving the design of SBCCs.

The rest of the chapter is organized as follows. In the next section we review related literature. Section 2.3 sets forth our model. In section 2.4 and 2.5, we analyze the optimal prize structure problem and contest structure problem respectively. Section 2.6 discusses some extensions of the model.

2.2 Related Literature

The use of skill-based user contests as a promotion vehicle is mentioned in most popular marketing texts. Consumer contests, sweepstakes, games are collectively called prize promotions. The difference between sweepstakes and SBCCs is mainly that sweepstakes are "game of luck" while SBCCs are "game of skill". The different between games and SBCCs is that games do not reward users on a relative performance basis. Despite its wide use, SBCCs have received little academic attention in the sales promotion literature with the exception of Ward and Hill (1991). Ward and Hill took a cognitive and social psychology perspective to the design of SBCCs, which contrasts with the economics perspective presented in this research. Few consultants or journalists have written on the design of SBCCs (e.g. Feinman et al 1986 and Howard 1988).

Our research is related to three bodies of literature on contests: relative compensation literature, R&D tournaments literature, and rent-seeking literature. Relative compensation (some times called tournaments or contests) is often used in compensating fund managers and sales representatives. Since the original paper by Lazear and Rosen (1981), relative compensation scheme has received considerable attention in economics (e.g. Nalebuff and Stiglitz 1983), marketing (e.g. Basu et al 1985) and finance (e.g. Brown et al 2001) literature. A majority of papers in this literature focus on comparing relative compensation with commonly-used piece-rate compensation. A few recent papers, including Kalra and Shi (2001) and Krishna and Morgan (1998), took the relative compensation scheme as given and studied the design of it. However, relative compensation literature usually assumes maximizing aggregate output. Therefore, their results are not directly applicable to the online entertainment context.

R&D tournaments (also called research contests) are frequently used by governments or other public sectors to nurture innovation. Select the *best* innovation is a distinctive objective of R&D tournaments. A major design issue studied in R&D tournaments literature is the issue of entry policy. Taylor (1995) studied the number of candidates. Fullerton and McAfee (1999) proposed using auctions to screen candidates. The prize structure is not an issue in this literature since there is normally one winner.

Tullock (1981) originated the rent-seeking literature by modeling rent-seeking activities (e.g. lobbying for monopoly rights) as all-pay auctions. A major distinction between all-pay auctions and winner-pay auctions is that in all-pay auctions, the bids are not refundable independent of winning. The main concern in this literature is whether the aggregate expenditure exceeds the total rent to be allocated. The rent-seeking literature is joint by auction theorists. The most recent development on the all-pay auction approach to contests includes Moldovanu and Sela (2001, 2002) and Che and Gale (2000, 2003). Our model of SBCCs also adopts the all-pay auction approach to contests.

Krishna and Morgan (1998) and Kalra and Shi (2001) studied the issue of optimal prize structure in the context of employee compensation. Krishna and Morgan (1998) show that when employees are risk-neutral, winner-take-all is optimal; winner-take-all is also optimal in two-player or three-player contests, regardless of employees' risk-attitude and the distribution of the output. Kalra and Shi (2001) analyzed the optimal prize structure in a multiple-player context. They showed that when sales follow uniform distribution, the winner-take-all is optimal regardless of the number of salespersons, their risk attitude, and the degree of uncertainty; however, if sales follow logistic distribution multiple prizes should be awarded and the optimal number of prizes increases and the optimal inter-prize spread decreases with the degree of risk aversion. Both papers have assumed identical employees.

Singh and Wittman (1998) studied the issue of prize structure with heterogonous contestants. They modeled both heterogeneous skills and *stochastic* performance, whereas in this research we assume *deterministic* performance. Their model assumed only two players therefore is not suitable for studying SBCCs. With uniformly distributed skill, they showed that the optimal prize is the highest when the designer maximizes the winner's performance, the second highest when the designer maximizes average performance and the lowest when the designer maximizes loser's performance[3].

Glazer and Hassin (1988) and Moldovanu and Sela (2001) are closest to this research. They studied the issue of optimal prize structure in a similar framework as this research but with different design objectives. In particular, both papers assume the designer maximizes aggregate output of the contestants. Glazer and Hassin (1998) showed that Winner-Take-All is optimal under uniformly-distributed skills and linear cost functions. Moldovanu and Sela (2001) generalized Glazer and Hassin (1998)'s Winner-Take-All result to general

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[3] In their paper, the three design objectives correspond to patent race, salespersons contests, and sports contest respectively.

distributions. They showed that if the cost function is linear or concave, winner-take-all is optimal regardless of the distribution of abilities and the number of players. As we show later, their results do not carry over to SBCCs in general. Also, because the optimal prize structure obtained in their settings is an extreme Winner-Take-All structure, they didn't offer insights on how factors such as skill distribution and contest size affect the number and allocation of prizes.

Optimal entry policy has been studied in the R&D tournament literature. Taylor (1995) showed that open entry is generally not optimal even if the cost of running contests is zero. They argued that with too many participants, contestants are discouraged from spending effort because each of them has a smaller chance to win. Fullerton and McAfee (1999) showed that it is often optimal to allow just two lowest-cost firms to participate. Clearly, the *two-is-optimal* result may not apply in SBCCs due to different design objectives.

The segmentation issue is recently studied by Moldovanu and Sela (2002). They compared a grand contest with k parallel contests with the equally-split prizes. They found that when the contestants' cost functions are linear or concave, the aggregate output of a grand contest dominates that of k parallel contests. Their result contrasts with our horizontal segmentation results – in our setting a grand contest dominates k parallel contests *only under certain conditions*.

The concept of handicapping in this research is different from those studied in prior literature. Lazear and Rosen (1981) studied a handicapping system which gives high-skilled employee a harder start. Feess et al (2003) and Clark and Riis (2000) studied a similar handicapping system in the context of rent-seeking games, in which the rule of allocation is in favor of one bidder against the other (e.g. between a local bidder an international bidder). Both approaches require information on type of contestants and impose "unfair" rules based on observed types. In our research, however, the contest designer can handicap high-skilled users by implementing a performance function that has higher marginal rate of substitution of usage for skill. The handicapping approach presented in this research is based on "fair rules" and can be implemented without the knowledge of actual skills.

2.3 A Game-theoretic Model of Skill-Based Contests

We consider a company which sells a single service to n users indexed by $i = 1, 2, ..., n$ (we will drop the subscription i whenever we talk about any one user). In order to promote its service, the company organizes a one-time SBCC among the n users. So each of the n users is a potential participant of the SBCC.

The SBCC is tied to the service in the way that the amount of the service consumed by the user (hereafter *usage*) will enhance a user's *performance* in the SBCC. A certain skill factor also affects a user's performance in the SBCC. The skill factor could be writing skill in a short essay contest or photography skill in a photo contest. We consider the skill factor as one-dimensional.

We assume a user's performance (x) depends on her usage (t) and skill (μ) in a function form $X(\mu,t)$, which we call the *performance function.* In particular,

$$X(\mu,t)=Q(\mu t), \text{ where } Q'(\cdot)>0 \text{ and } Q(0)=0.$$

It is straightforward to see that performance increases both in skill and in usage. We can also see $t=\frac{1}{\mu}Q^{-1}(x)$ is the required usage for reaching performance x . Note that we don't restrict the functional form of $Q(\cdot)$. The essential assumption is the multiplicative relationship between usage and skill, which enables us to obtain an explicit solution later[4].

We consider the skill factor as an endowed characteristic of a user. Each user's skill parameter is drawn independently from a common skill distribution $F(\mu)$ with the density function $f(\mu)$. We assume $F(\mu)$ has a fixed support $\left[\underline{\mu},\overline{\mu}\right]$, $F(\mu)$ is atomless, $f(\mu)>0$, and $f'(\mu)$ is bounded.

[4] Note that we can easily extend to the case of $t=\frac{1}{\varphi(\mu)}Q^{-1}(x)$ by redefining $\varphi(\mu)$ as skill.

We assume a user knows her own skill [5] and the common skill distribution $F(\cdot)$. But a user does not know other users' skill or performance when deciding on her usage level.

The company awards the prizes based on the rank-order of users' performance. We assume the company has a fixed prize budget for the SBCC, normalized to 1. The company can award at most n prizes. Denote $(v_1, v_2, ..., v_n)$ as a *prize structure*. It must be that

$$\sum_{j=1}^{n} v_j = 1 \text{ and } v_1 \geq v_2 \geq ... \geq v_n \geq 0. \qquad (1)$$

Users

We assume a user's utility from winning jth prize is v_j [6]. We consider a user's utility from the usage as θt [7]. At the same time, she has to make a payment pt to the company. We are interested in the case where the net utility from each unit of usage is negative, i.e. $\theta < p$. Such a case can arise in two scenarios: 1) the

[5] It is not uncommon that a user may overestimate or underestimate her own skill. However, our analysis should generally hold if users do not over-estimate or under-estimate their skills in a systematic way.

[6] A user may get more than the monetary value of a prize by deriving emotional values from winning a prize (Ward and Hill 1991). These factors are not considered in this research.

[7] In section 6, we discuss the cases when marginal disutility of usage increases or decreases.

company tries to attract users who wouldn't consume the service if there is no prizes. 2) The company tries to enhance the sales among existing customers, who wouldn’t have consumed as much if there are no prizes. In both scenarios, the user’s net payoff from an additional unit of usage (if we don’t consider the prize utility) is negative. In the second scenario, we should interpret t as the *incremental* usage due to the SBCC.

In our model, all users maximize their expected utility and their utility functions are identical. In particular, when a user's probability of winning prize j is p_j and her usage is t, her total utility is

$$\sum_{j=1}^{n-1} p_j v_j - pt + \theta t \qquad (2)$$

The Firm

We assume that at the point of designing the SBCC the company is uninformed about users' skill parameters. So from the company point of view a user's usage is a random variable. The expected profit from a user is $E[pt(\mu)]$ and the total revenue from a SBCC is $nE[pt(\mu)]$.

We assume that the company’s marginal cost of service is zero (the case of linear marginal cost is similar). The company incurs a fixed cost K for administrating the SBCC. K may consist of the cost for prizes, the cost for advertising and other administrative cost.

$$\pi = nE[t(\mu)] - K \qquad (3)$$

Because K does not affect any of the design problems below, we can drop K from the company's objective function. But we still call π as the company's expected profit.

The SBCC Game

The SBCC game unfolds as following. Before the SBCC starts, the company announces the prize structure and the rule of the SBCC. Meanwhile, each user learns their private skill parameter μ , the common (prior) distribution $F(\cdot)$, and the number of potential participants n . When the SBCC starts, each user simultaneously and independently chooses her usage t and their performance is jointly determined by their usage and skill. Then the company will evaluate each user's performance and awards prizes according to the announced rule.

It is worth pointing out that, the framework described above can also be applied to participation campaigns, such as encouraging users to write product reviews or testimonies, to provide feedback to services, and to exchange their experience about using the products. These user activities, while not generate direct revenue to the company, contribute to create and enhance user values. A SBCC may play a role in stimulating larger amount of user participation in these campaigns. By simply re-labeling variables, our model can accommodate the SBCCs used in these contexts as well. But in order to avoid confusion, we stick to the terminology that we use for the sales promotion context.

The Equilibrium Usage

A user's strategy involves choosing her usage level based on her skill μ and other public information. We only consider the *symmetric strategy equilibrium*, in the sense that users with the same skill will choose the same level of usage in equilibrium. Let $t(\mu)$ denote the equilibrium mapping from one's skill to usage. Note that a symmetric strategy implies all users adopt the same $t(\mu)$ but it doesn't mean each user ends up with same level of usage. As usual, we consider the *Nash* equilibrium strategy, i.e. if all other users adopts $t(\mu)$ then one's optimal strategy is also to adopt $t(\mu)$.

Proposition 1 *(Equilibrium Usage)* [8] *There is a unique symmetric equilibrium performance strategy for a SBCC,*

$$t(\mu) = \frac{1}{p-\theta} \sum_{j=1}^{n} \delta_j \left[\frac{1}{\mu} \int_{\underline{\mu}}^{\mu} \sigma \omega_j{}'(\sigma) d\sigma \right] \qquad (4)$$

where $\delta_j = j(v_j - v_{j+1})$ *is the prize money allocated to* j *th prize differential and* $\omega_j(\sigma) = \frac{1}{j} F_{n-j\,:\,n-1}(\sigma)$ *is the consumer's expected share of* δ_j *in equilibrium.*

According to proposition 1, the equilibrium usage increases in the utility from usage. But the equilibrium usage may not necessarily increase in skill, despite the fact that equilibrium performance always increases in skill (see

[8] All proofs are in the appendix.

Appendix A3). In other words, in SBCCs a user may have high performance but not-so-high usage.

It is also worth noting that the equilibrium usage is not affected by $Q(\cdot)$, which means that any order-preserving manipulation of the performance numbers will not have any effect on the equilibrium usage or profit. Such a property reflects the company's objective being maximizing users' input and it distinguishes SBCCs from other output-oriented contests.

2.4 Optimal Prize Structure

2.4.1 The Optimal Prize Structure Problem

Note that in equilibrium $y = t(\mu)$, plug (*4*) into (3), we can obtain the company's expected profit

$$\pi = \frac{np}{p-\theta}\sum_{j=1}^{n-1}\delta_j\left[\int_{\underline{\mu}}^{\bar{\mu}}\frac{1}{\mu}\int_{\underline{\mu}}^{\mu}\sigma\omega_j{}'(\sigma)d\sigma f(\mu)d\mu\right] \qquad (5)$$

Let

$$\varepsilon_j = \frac{np}{p-\theta}\int_{\underline{\mu}}^{\bar{\mu}}\frac{1}{\mu}\int_{\underline{\mu}}^{\mu}\sigma\omega_j{}'(\sigma)d\sigma f(\mu)d\mu \qquad (6)$$

denote the marginal profit from j-th prize differential. Note that the prize budget constraint (1) now writes

$$\sum_{j=1}^{n-1}\delta_j = 1 \text{ and } \delta_j \geq 0, \forall j \qquad (7)$$

The optimal prize structure problem becomes,

$$\max_{\{\delta_1,\delta_2,\ldots\delta_{n-1}\}} \pi = \sum_{j=1}^{n-1} \delta_j \varepsilon_j \qquad (8)$$

s.t. (7)

For an example of prize allocation in prize differentials, if the company allocates the entire prize sum 1 to δ_5 , then the resulted prize structure is $v_1 = v_2 = v_3 = v_4 = v_5 = 0.2$. For another example, if the company allocates 0.8 to δ_1 and 0.2 to δ_2 , then the resulted prize structure is $v_1 = 0.9, v_2 = 0.1$.

Proposition 2 *(Optimal Prize Structure): The solution to the problem (*8*) is to split the prize sum equally among the first j^* winners, where $j^* \in \left\{ j \mid \varepsilon_j \geq \varepsilon_k \right\}$.*

Proposition 2 states that companies should always spend their prize money to the most productive prize differential. The resulted prize structure can be either one grand prize, which we call a *Winner-Take-All* structure or $j^* \geq 2$ equal-sized prizes, which we call a *Split-Prize* structure.

The remaining question is how a company should choose between a Winner-Take-All prize structure and a Split-Prize structure. Unfortunately there is no unconditional answer to this question. The optimal prize structure depends on both the number of potential users and the distribution of skill levels. Recall that the optimal prize structure depends on the size of ε_j 's, which in turn depend both on the skill distribution $F(\cdot)$ and the size of contest (refer to 666). The following examples demonstrate that both Winner-Take-All and Split-Prize can be optimal.

Example 1: (Winner-Take-All) Skill is uniformly distributed on [1, 2]. $n=5$, $\theta=0$ and $p=1$. The values of ε_1 to ε_4 are $0.91, 0.86, 0.81,$ and 0.75 respectively Thus, the optimal number of prizes is 1.

Example 2 (Split-Prize) Skill follows Cauchy distribution on $[1,2]$, with the location parameter $t=1.5$ and the scale parameter $s=0.02$. $n=5$, $\theta=0$ and $p=1$. Computation shows ε_1 to ε_4 are $0.967, 0.971, 0.968,$ and 0.939 respectively. The optimal number of prizes is 2.

Fortunately, we are able to characterize conditions for Winner-Take-All in terms of the distribution of skill and the size of the contest. We show in the following that Winner-Take-All is *often* optimal.

2.4.2 A distribution condition for Winner-Take-All

Proposition 3 *(Distribution Condition) A Winner-Take-All prize structure is optimal if the skill distribution satisfies*

$$\frac{f(\sigma)}{\int_{\sigma}^{\bar{\mu}} \frac{1}{\mu} f(\mu)\,d\mu} \text{ increases in } \sigma \text{ on } [\underline{\mu}, \bar{\mu}] \qquad (9)$$

An immediate implication of Proposition 3 is that the entire class of hazard-rate-increasing distributions[9] satisfies (*9*), including uniform, normal, logistic, exponential, and etc (a proof is included in Appendix A7). It appears that with a wide range of distributions which we regard as normal, the Winner-Take-All structure should be the optimal.

Proposition 3 states that if the distribution of skill displays hazard-rate-increasing property, the company should go for the Winner-Take-All prize structure, no matter what size of the contest is. To understand the reason behind the proposition, we need to consider how the prize allocation affects users of different skill. In the following figure, we depict marginal profit of the first and the second prize differentials with respect to different skill levels. We can see a differential between the first and the second prize generates more profit from high-skilled users and less from low-skilled users, compared with a differential between the second and the third prize. Hazard-rate-increasing condition ensures that overall profit from an increase in the first prize differential is larger than that in the second prize differential. In fact, the same condition ensures the first prize

[9] In our case, hazard rate is interpreted as the rate of elimination, i.e. the conditional probability of eliminating an opponent. For more technical details on hazard-rate-increasing distributions, please refer to, e.g., Bagnoli and Bergstrom 1989.

differential dominates every other prize differential in terms of overall marginal profit.

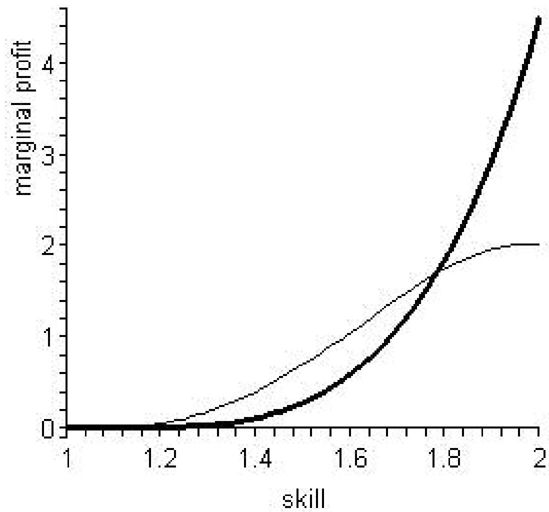

Figure 8. Marginal Profit of the First and the Second Prize Differential

by Skill Level, n=5.

An important message for designers of SBCCs is that it is wrong to look at the sheer size of population on each skill-segment when deciding the optimal prize structure. One may intuitively think that when there are more low-skilled users, the company should award more prizes to appeal to them. However, one has ignored the fact that these low-skilled users are less interested to compete because there are more of them. Instead the companies should pay attention to the hazard rate. Only if the hazard-rate for the low-skilled users is higher than that of high-skilled users, the company should consider giving more prizes. Proposition 3 also suggests to the practioners that it is often more profitable to appeal to high-skilled segment than low-skilled segment through a Winner-Take-All prize structure.

2.4.3 A Size Condition for Winner-Take-All

We need an additional assumption on the regularity of the distribution to proceed.

Assumption: (regularity) $\exists \varepsilon > 0$, s.t. $f(\mu) \geq \varepsilon, \forall \mu$.

Proposition 4 *(Size Condition) If the regularity assumption holds, the Winner-Take-All prize structure is optimal for a sufficiently large* n .

The intuition behind this proposition is as following. When the size of the SBCC increases, the marginal profit from a low-skilled user vanishes more quickly than the marginal profit from a high-skilled user, which is true for all prize differentials. When n increases, low-skilled segment becomes increasingly irrelevant to the total marginal profit. Recall that the high-skilled segment is where a high-ranked prize differential has the advantage. As a result, when n is large enough, the first prize differential dominates all other prize differentials and Winner-Take-All becomes the optimal prize structure. Because SBCCs usually involve thousands of users, we think it is highly likely that proposition 4 will apply.

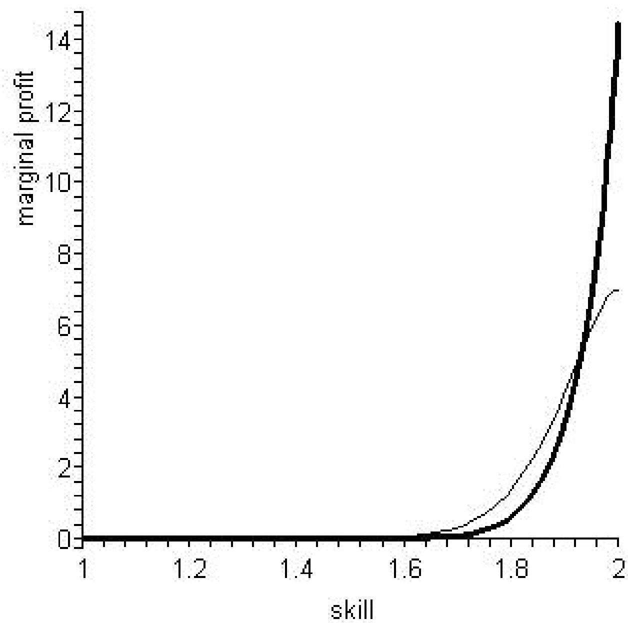

Figure 9. Marginal Profit of the First and the Second Prize Differential

by Skill Level, n=15.

Proposition 4 predicts that even for certain distributions the optimal prize structure is Split-Prize, it will eventually switch to Winner-Take-All as the size of contest becomes larger and larger. The following example verifies this prediction.

Example 3. Let $F(\mu)=(\mu-1)^{\frac{1}{4}}$. We tabulate the optimal number of prizes and expected profit when n goes from 5 to 8 below.

n	5	6	7	8
j^*	4	5	1	1
π	0.841	0.845	0.850	0.860

Table 1: Effect of Size on Optimal Prize Structure

To summarize this section, our main result is that Winner-Take-All is most likely optimal, despite a SBCC may admit either Winner-Take-All or Split-Prize as its optimal prize structure. Proposition 3 and proposition 4 shed light on how the distribution factor and the size factor will affect the tradeoff between high-skilled users and low-skilled users. They provide important guidance on the choice of optimal prize structure.

One may contemplate whether the optimal number of prizes in a SBCC has an upper bound -- for instance, Kalra and Shi (2001) have found in there model context that the number of prizes should not exceed 50% of the number of contestants. However, such an upper bound does not exist in our context. A piece of evidence is in example 3: note that when n = 6, the optimal number of prizes is 5.

2.4.4 SBCCs with reservation utility

The main part of our analysis assumes a friction-free environment in the sense that users don't incur any upfront cost to participate a SBCC. Now we extend the analysis to a context with frictions on the user part, which we model as a fixed reservation utility R for all users. R can be interpreted as any entry cost, which one incurs upon participation, e.g. spend time learning the rules of the SBCC or registering herself as a participant. Since such a cost can be avoided if one does not participate in the SBCC, a user will expect she get at least R by participating.

The following proposition extends our previous results on the optimal prize structure to this case.

Proposition 9 *(Optimal Prize Structure with Reservation Utility) If Winner-Take-All is the optimal prize structure for a contest without reservation utility, so it is for a contest with a reservation utility* $R > 0$.

2.5 Contest Structure

In this section we study several other decision variables in SBCC design. We start by analyzing the impact of the size of user population and the skill distribution on users' usage and the company's profit. We then study the segmentation and the entry fee issues. These analyses provide important insights for such practical questions as whether a company should hold SBCCs at different skill levels and whether a company should hold regional SBCCs instead of a global one.

2.5.1 The Impact of Size on Profit

Proposition 5 *(Size and Profit) If the Distribution Condition or the Size Condition is satisfied, the company's profit increases in* n *. However, the total expected profit does not exceed* $\frac{p}{p-\theta}$.

When adding an additional participant, the direct effect is she will make additional usage. The indirect effect is that she causes others to lower their usage levels. This proposition implies that the direct effect is stronger than indirect effect, but as n becomes larger, the gap between two effects converges to zero. The following figure illustrates the profit trend predicted by proposition 5 (assuming a Winner-Take-All prize structure and skill is uniformly distributed on [0.5, 1]).

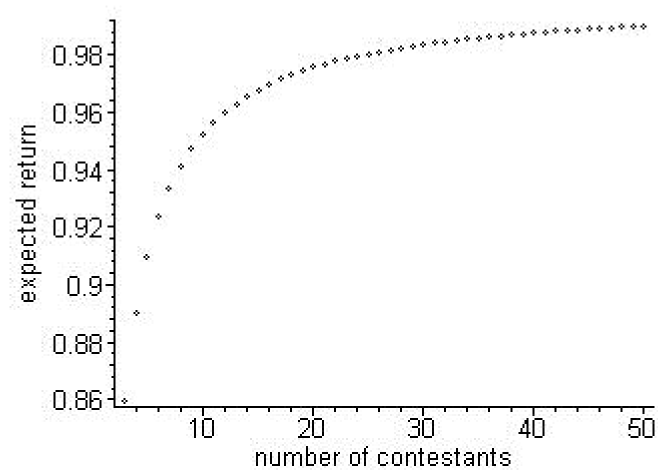

Figure 10. Effect of Size on Expected profit

Proposition 5 implies that for a given prize budget the company cannot infinitely increase its profit by expanding the pool of potential participants, even if we do not consider the cost of doing so. In practice there is always additional cost for administrating a larger SBCC. For instance, processing more contest entries will require more labor hours and/or more computer facility; the advertising expenditure will also be higher for a larger SBCC campaign. In such a case, a company has to tradeoff the decreasing marginal profit with the non-trivial cost of admitting one more user. Thus, there will be an optimal size for a SBCC beyond which point a company will lose money.

2.5.2 The Impact of the Skill Distribution on Profit

Although a company cannot change the skill of a user, it can however influence the skill distribution of a SBCC through, say, segmentation (e.g. professional group and amateur group) and admission policies. Therefore, it is necessary to understand the how the skill distribution affects the company's profits. It is worth pointing out that despite obvious relevance of this issue to the practice, to our best knowledge there is no prior research directly addressing such an issue in a general distribution case as we do.

Proposition 6 *(Skill Distribution and Profit) Consider two SBCCs* $\mathbf{C}_1$ *with skill distribution* $F(\cdot)$ *and* $\mathbf{C}_2$ *with skill distribution* $G(\cdot)$ *.They are the same otherwise. Denote* $F^{-1}(\cdot)$ *(* $G^{-1}(\cdot)$ *) as inverse distribution function*[10] *for* $F(\cdot)$ *(*$G(\cdot)$ *) and denote* $t_1(u)$ *(*$t_2(u)$ *) be the equilibrium usage in* $\mathbf{C}_1$ *(*$\mathbf{C}_2$ *) for a user with skill* $F^{-1}(u)$ *(*$G^{-1}(u)$ *). If*

$$\frac{F^{-1}(u)}{F^{-1}(s)} < \frac{G^{-1}(u)}{G^{-1}(s)}, \forall 0 \le s < u \le 1, \qquad (10)$$

[10] Formally, $F^{-1}(u) = \sup\{\mu : F(\mu) \le u\}$. An inverse distribution function maps a value of the underlying variable to a percentage.

then for any $0 < u < 1$ *,* $t_1(u) > t_2(u)$ *. Furthermore,* $\mathbf{C}_1$ *generates higher profit than* $\mathbf{C}_2$ *.*

Note that $F^{-1}(u)/F^{-1}(s)$ measures the inequality of skills between two skill levels u and s . For instance, if $u = 80\%$ and $s = 50\%$, then $F^{-1}(u)/F^{-1}(s)$ is the ratio of skill between a user whose skill is higher than 80% and a user whose skill is higher than 50% . Proposition 6 states that if $F(\cdot)$ displays systematically lower inequality than $G(\cdot)$, then a user in $\mathbf{C}_1$ will consume more than a corresponding user (i.e. a user at the same skill percentage) in $\mathbf{C}_2$. In other words, in a more matched-up SBCC users compete *systematically* more fiercely for prizes. It is also worth noting that Proposition 6 predicts that not only a company who maximizes total usage will prefer $\mathbf{C}_1$ to $\mathbf{C}_2$, but also any company whose objective function is an increasing function of total usage.

We use the following stylized examples to discuss the implications of proposition 6.

Example 4. (a). Let F be a uniform distribution on $[a,b]$ and G be a uniform distribution on $[5,6]$. $\frac{F^{-1}(u)}{F^{-1}(s)} = \frac{1+u}{1+s} > \frac{G^{-1}(u)}{G^{-1}(s)} = \frac{5+u}{5+s}$. So we conclude that F generates lower profit than G .

(b). Let F be an arbitrary distribution on $[a,b]$, and G be a distribution on $[2a,2b]$ and $G(x) = F(2x)$. $\frac{G^{-1}(u)}{G^{-1}(s)} = \frac{2F^{-1}(u)}{2F^{-1}(s)} = \frac{F^{-1}(u)}{F^{-1}(s)}$. We conclude that F

generates equal profit as G and this conclusion can be verified through conventional method.

(c). Let F be an arbitrary distribution on $[a,b]$, and G be a distribution on $[a^2,b^2]$ and $G(x)=F(x^2)$. Because $\frac{G^{-1}(u)}{G^{-1}(s)}=\left(\frac{F^{-1}(u)}{F^{-1}(s)}\right)^2>\frac{F^{-1}(u)}{F^{-1}(s)}$. We conclude that F generates higher profit than G .

The above examples can be interpreted as a repeated SBCC environment where every user gains their skills overtime. If every user gains skill by the same amount (case a), the company is better off since the ratio of skill between u and s decreases. However, if the user's skill level increases proportionally (case b), the company's profit is invariant. If the users gain their skill in a convex fashion (case c), the company is worse off because basically now u has even more advantage over s . Conversely, if the users gain their skill in a concave fashion (the converse of case c), the company will be better off. To this end, a company has an incentive to help low-skilled customer learn faster to make a more competitive SBCC.

We can also view Proposition 6 from a different angle. Consider let $G^{-1}(u)=\phi(F^{-1}(\mu))$, we can see that a SBCC with distribution $G(\cdot)$ and a performance function $X(\mu,t)$ and a contest with distribution $F(\cdot)$ and a performance function $X(\phi(\mu),t)$ are in fact equivalent. By this alternative view, we can get additional insight from Proposition 6.

Corollary 1 *(Performance function) Consider a SBCC* $\mathbf{C}_1$ *with performance function* $X(\mu,t)$ *and a SBCC* $\mathbf{C}_2$ *with performance function* $\hat{X}(\mu,t)$ *. Assume* $\hat{X}(\mu,t) = X(\phi(\mu),t) = Q(t\phi(\mu))$ *. The two SBCCs are the same otherwise.* $\mathbf{C}_1$ *generates higher profit than* $\mathbf{C}_2$ *if the marginal rate of substitution of usage for skill (MRS) in* $\mathbf{C}_1$ *is higher than that in* $\mathbf{C}_2$ *, i.e.*

$$\frac{X_t(t,\mu)}{X_\mu(t,\mu)} > \frac{\hat{X}_t(t,\mu)}{\hat{X}_\mu(t,\mu)}, \forall t,\mu \qquad (11)$$

According to corollary 3, if the company can choose a SBCC performance function that permits usage as a stronger substitute for skill, then the company can get higher profit from the SBCC. By doing this, the company essentially handicaps the high-skilled users --- although they still have the same level of skill as before, they have less advantage over the low-skilled users.

2.5.3 Segmentation of the Population

Real world contests often further segment participants into smaller groups. NBA holds regional conferences before the finals. The Mobile Millionaire contest classifies players into four stages based on their experience and past performance. The question is whether these segmentation strategies will generate more profit for companies in the SBCC context. We consider segmentation in two categories: segmentation based on the skill factor, which we call the *vertical segmentation,* and segmentation based on non-skill factors such as geographic regions, which we call the *horizontal segmentation*.

In horizontal segmentation we assume the skill distribution for each segment is the same as the whole population. Therefore the SBCC for each segment resembles the SBCC for the entire population except that it has smaller size. Proposition 5 predicts that when everything is the same (including the prize budget), a smaller SBCC generates less profit than a larger SBCC under the Distribution Condition or the Size Condition. We can quickly conclude that given the same prize budget, the company can not get higher profits by horizontal segmentation.

For the case of vertical segmentation, we assume that the company can separate the users into a high-skill group and a low-skill group, e.g. through some qualifications or past performance. Such a segmentation strategy will cause the skill distribution for each segment to be different that of the original population. Consequently, both size effect (Proposition 5) and the distribution effect (Proposition 6) apply. While reducing the size of contest will reduce the expected profit, grouping users by skill may raise the usage level and therefore the expected profit. The following example shows it is possible to raise the overall expected profit by a vertical segmentation.

Example 5: (Vertical Segmentation) Consider a non-segmented SBCC $\mathbf{C}_0$ with 20 users and two vertically-segmented SBCCs $\mathbf{C}_1$ and $\mathbf{C}_2$ with 10 users each. Assume the skill distribution for $\mathbf{C}_0$ is uniform distribution on [1, 2] and the skill distribution for $\mathbf{C}_1$ and $\mathbf{C}_2$ are uniform distributions on [1, 1.5] and [1.5, 2] respectively. We still assume the reservation utility $\theta = 0$. The company has a prize budget 1 for $\mathbf{C}_0$ and it allocates 0.75 and 0.25 to $\mathbf{C}_1$ and $\mathbf{C}_2$ respectively. Our computation shows that the expected profit from $\mathbf{C}_0$ is 0.9756, while the aggregate expected profit from $\mathbf{C}_1$ and $\mathbf{C}_2$ is 0.9797.

Proposition 7 *(Segmentation) Assume the Distribution Condition or the Size Condition is satisfied and the prize budget is fixed. The company can not get higher profit through horizontal segmentation but may get higher profit through vertical segmentation.*

2.5.4 Entry fee

Charging an entry fee causes three effects: a) it excludes low-skilled users whose utility of participation is low. b) It affects the equilibrium consumption of participating users. c) Entry fee itself becomes an additional source of revenue for the company. Below we analyze the overall effect of charging an entry fee. In order to simplify the derivation, we focus on the Winner-Take-All case.

Proposition 8 (Entry Fee) *For a given entry fee E, the marginal user (μ_e), i.e. the user who is indifferent between participating and not participating, is the solution to*

$$\frac{1}{p-\theta}F_{n-1:n-1}(\mu_e)=E\ .$$

If $\frac{\theta}{p}<1-\int_{\underline{\mu}}^{\bar{\mu}}\frac{\underline{\mu}}{\mu}f(\mu)d\mu$ *, the company should charge an optimal entry fee. The corresponding optimal marginal user* μ_e^* *is the solution to*

$$\int_{\mu_e^*}^{\bar{\mu}}\left(\frac{n}{n-1}-\frac{p}{p-\theta}\frac{\mu_e^*}{\mu}\right)f(\mu)d\mu=\frac{1}{n-1}$$

If $\frac{\theta}{p}$ *is high enough, the company should charge no entry fee.*

By this proposition, charging an entry fee may increase the company's profits. Whether or not to charge an entry fee depends on the size of user's intrinsic utility relative to their payment. If the intrinsic utility is very low, excluding low-skilled users through an entry fee is profitable because an entry fee allows the company to extract more surplus from the participating users. Note that part of the revenue from participating users is entry fee. In other words, the company swaps part of the consumption revenue with entry fee revenue by charging an entry fee. Such a swap is not worthwhile when the intrinsic utility is high because entry fee revenue does not capture intrinsic utility. Therefore, when the intrinsic utility from consumption is high, it is no longer profitable to charge an entry fee.

2.6 Extensions

2.6.1 Maximizing the number of participants

Sometimes, the objective of SBCCs leans more toward promotes the awareness of product from the broadest audience rather than directly targeting on the total profit. In such case, maximizing the number of participants becomes the company's objective. When there is no reservation utility, all users will participant no matter what -- so the issue of prize structure becomes irrelevant to this objective. When there is reservation utility, however, we have to consider what prize structure attracts the maximum number of users. We analyze the latter case below.

Assume there is a reservation utility $R > 0$. Let μ_0 be the cutoff skill level μ_0 below which no user will participate. Similar to the entry fee case, μ_0 is the solution to

$$\frac{1}{p-\theta}\sum_{j=0}^{n-1}\delta_j\omega_j(\mu) = R \quad (14)$$

Because the company maximizes the number of participating users, it wants the μ_0 as low as possible. Note that the $\omega_j(\mu)$ increases in μ , in order to keep μ_0 low, the company should assign the entire prize sum to the prize differential with the highest coefficient.

Proposition 10 *(Prize Structure That Maximizes Participation) Let* $\omega(\mu)$ *be the upper envelope of the function family* $\{\omega_j(\mu), j = 1..n-1\}$ *. In order to maximize the number of participants, the company should optimally give* j^* *equal-sized prizes where* j^* *is the subscript of the function on the envelope at* μ^* *and* μ^* *solves* $R = \omega(\mu)$ *. Moreover, the optimal number of prizes* j^* *decreases in* R *and in* n *and is independent of skill distribution* $F(\cdot)$ *.*

In the following figure, we illustrate the envelope of $\omega_1(\mu)$ to $\omega_9(\mu)$ in a SBCC with 10 potential contestants.

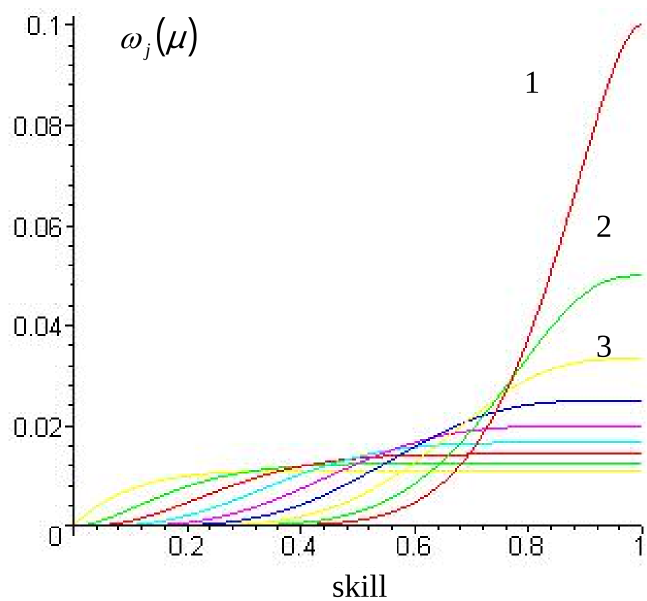

Figure 11. Prize structure when maximizing the number of participants

2.6.2 Skill-Based Contests with Non-Linear Cost

We consider a case where the net disutility from usage can be convex or concave. For simplicity, we consider the class of disutility functions, θt^{α} . Following the steps in Proposition 1, we can obtain the new equilibrium usage,

$$t(\mu)=\frac{1}{\mu}\left(\frac{1}{p-\theta}\sum\delta_j\int_{\underline{\mu}}^{\mu}\omega_j'(\sigma)\sigma^{\alpha}d\sigma\right)^{1/\alpha} \quad (15)$$

The following picture illustrates how the degree of concavity affects equilibrium usage at different skill levels.

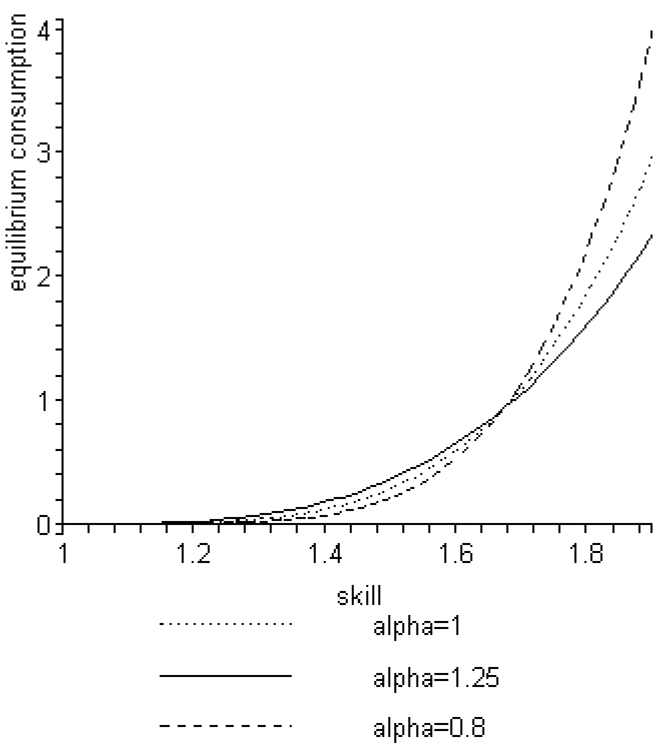

Figure 12. Equilibrium Usage and α

As we can see when the concavity increases, high-skilled users compete less aggressively. Intuitively, high-ranked prizes, which appeal high-skilled users the most, become less effective. Thus the optimal prize structure tends to allocate more to the low-ranked prizes. We use the following example to verify this intuition.

Example 7: (optimal prize structure and concavity of disutility) we assume the company can offer a maximum of two prizes. When $\alpha = 0.5$, the expected profit under Winner-Take-All and Split-Prize are 0.50 and 0.30 respectively. Winner-Take-All is optimal. When $\alpha = 3$, however, the expected profit under Winner-Take-All and Split-Prize are 1.98 and 2.19 respectively. Split-Prize is optimal. It is worth noting that a non-equal-sized prize structure may be optimal. For instance, when $\alpha_1 = 1.25$, we find that the optimal prize structure is a 0.65/0.35 split between the first and second prize.

While the optimal prize structure in nonlinear disutility case is generally more complicated to determine, the basic intuition in the above example applies to more general case.

Chapter 3. An Empirical Analysis of Status Seeking in Mobile Gaming

In chapter 1 we argued that users in online entertainment communities not only derive intrinsic utility from consuming the online entertainment service but also the value of status by obtaining a superior performance relative their peers. In this chapter, we empirically verify whether status seeking behavior is a driving force in mobile gaming using a mobile gaming dataset. By studying status seeking behavior, we hope to enhance our understanding of users' playing patterns and provide a diagnosis for the current design of the mobile game.

A major challenge of studying status seeking is that the effect of status seeking may be compounded with that of other factors. At the first sight, a user may play a game as much because it is fun as because she is pursuing a status among her peers. Similarly, a user may stop playing because she is no longer having fun or she is not interested in seeking status. A further examination helps us to differentiate these two driving forces.

The status seeking perspective suggests that a user will devote effort to achieve a satisfying status. She will stop if the status is reached and she will continue trying if the target status is not reached and her effort has not yet reach a threshold level. Such a behavior presumption is consistent with our theoretical model in chapter two, where a user will choose a target performance level and achieve that by choosing a certain level of effort (except that here we take the uncertain outcome in consideration). If the user follows such a behavior pattern, she tends not to stop if she gets a low score and to stop if she gets a high score. In contrary, the intrinsic utility perspective suggests that an unsatisfying experience will cause the user to stop while a satisfying experience will cause the user not to stop, were users to base her calculations of the expected utility of the next game on her past experience. By such an argument, a user will tend to continue to play if she gets a high score and to stop if she gets a low score. Such a contrast forms our basis for testing status seeking behavior.

3.1 Data

The dataset we have is users' playing records in the Mobile Millionaire game. The data was collected by a European wireless operator. The game was launched in October 2001 on the SMS (short message) platform. The dataset contains game-by-game playing data of all active users over a 7-month period from February 2003 to August 2003.

Mobile Millionaire is a quiz game played via cell phone. Players' objective is to correctly answer trivia questions served by game server through wireless networks to progress up the virtual money tree. In the version of game we study, a player has to answer a total of 15 questions to reach the 1,000,000 points, the highest one could reach. The player has to answer the current question correctly to proceed with a new question. If a user picks the wrong answer, the game ends. Like the TV millionaire, the question 3 and the question 5 are safe heavens in the game (see the table below). If a player answers wrong above a safe heaven, she will get the points of the safe heaven level instead of getting 0. One can also choose to walk away to secure the points she currently have.

We recoded game points in the dataset according to the number of correct answers one has to answer correctly in a row in order to reach that game points (refer to table 2). Using the recoded game points for regression has an advantage over the original point scheme: the coefficient for recoded game points represents the marginal effect of one more step in the virtual money tree.

Points	Questions	Score(Recoded)
1,000,000	15	4
500000	14	3
250000	13	3
125000	12	3
64000	11	3
32000	10 (Safe Heaven)	3
16000	9	2
8000	8	2
4000	7	2
2000	6	2
1000	5 (Safe Heaven)	2
500	4	1
300	3	1
200	2	1
100	1	1
0	0	0

Table 2. Game points and its coding

There are also 3 lifelines available for players, including a “50:50” lifeline which removes two wrong answers, an “asking the audience” lifeline which gives statistics on other players’ answers to the same question, and a “phone a friend” lifeline, which sends player a hint (by the server).

A player needs to send a short message to the server to initialize the game. After she starts playing, each of her requests and server’s responses take the form of short messages. Players pay the normal per-message fee but do not pay any premium charge for the game.

There are monthly prizes for top 5 players, each worth about $1450. In addition, the mobile network maintains a monthly hall of fame which is available to users through SMS or through the Internet.

According to game professionals, the game is usually played in a social context: a group of friends will play the game at the same time, each of them playing on their own phone.

A summary of the dataset over the seven month period is illustrated in table 3.

Number of games	97727
Number of sessions	54572
Number of (active) users	36418
Avg sessions per user	1.50
Avg games per user	2.68
Avg games per session	1.79
Avg points per game	2.10
Avg time per game	149 seconds

Table 3. Summary Statistics

3.2 Model Development

3.2.1 Choice of the dependent variable

Although our dataset permits the analysis of different variables including the number of games played (count), the interval between two games (duration), and the decision of continuing/stop (choice), we are most interested in studying the stopping decision made after each game, i.e. whether one would like to end this session.

A stream of binary decisions across a large number of individuals has been studied in other applications. Moe and Fader (2004) studied the conversion behavior in online shopping environment. In their model, the dataset consists of a stream of online store visits and associated purchase decision. The purchase decision in their context corresponds to the stop decision in our context. Other possible areas of application include new product trial (Fader et al 2003) and online search.

We recoded our dependent variable, *continue*, to be 0, if a user decided to end the session, and to be 1 otherwise. In order to identify a game session (i.e. a number of games played in a row), we have consulted a manager who is very knowledgeable about the game. Based on his input, we decided that if the interval between two consecutive games is longer than 60 minutes, the later game is considered as belonging to a new session. Due to the truncation of the dataset, the subsequent interval for the last game is defined as from the last game to the end of the month. Since the number of users who played at the very end of the month is only a small portion, the truncation problem is neglectable.

3.2.2 The Logistic Regression

Our basic model is a random utility model. Let U_{it} denote the user i's expected utility of playing the next game at game t and ε_{it} is an unobservable random term.

$$y_{it} = U_{it} + \varepsilon_{it}$$

A user will continue to play if $y_{it} > 0$ otherwise she will end the session. The probability of observing the user i to continue playing after playing game t is

$$\text{Prob}\{i \text{ continue at } t\} = \text{Prob}\{U_{it} + \varepsilon_{it} > 0\} = F(U_{it})$$

If we assume ε_{it} 's are independently distributed according to the logistic distribution, This leads to the familiar Logit model. The log-likelihood function for the above model is,

$$\log L = \sum_{it} \{continue_{it} \log F(U_{it}) + (1 - continue_{it}) \log(1 - F(U_{it}))\}$$

We consider U_{it} to be affected by the following components.

Baseline utility. For each user, there is a baseline expected utility of playing the game, independent of her past experience with the game. The baseline utility reflects the overall fun of playing the game.

Effect of near-term past performance. First of all, the users' past performance will alter her experience about the game thereby affect her expected utility of playing a next game. If a user has had a good play, she will adjust her expected utility upward. So we expect a good performance in current game will have a negative impact on the probability of stop.

Second, past performance also affects the expected gain of status for the next game. If a user has got a good performance in the last game, she has less to gain in the next game. Thus from status seeking perspective, her probability of continuing will decrease in past performance.

We tend to think status seeking dominates intrinsic utility in this game setting. One reason is that this game is not particularly fun to play compared with many other PC or console games. It is somewhat cumbersome because users have to memorize and type a handful of commands. Another reason is that this game is usually played in a social context, which implies that getting a low score would embarrass a user in front of others and getting a high score would bring her glory. For these reasons, we believe that the near term experience negatively affects the probability of continuing.

In our model, we use the score of last game (*score*) to approximate a user's near term experience. The sign of the coefficient will allow us to detect or reject status seeking hypothesis.

Effect of long-term past performance. Similar to near term performance, having a good performance in the past plays means the user is probably having fun, which in turn affects his expectation of the next play. Therefore, the intrinsic utility perspective suggests that the long-term performance to have a positive effect on the probability of stop.

The influence of status seeking, however, may not be as strong as in a short term. One reason is that a user may play with different friends at a different time, so that her past performance does not have much to do with her status in the current group. For these reasons, we hypothesize that intrinsic utility argument dominates in a long term so that the overall effect of the long-term performance is positive.

We use the average points collected in past games (*avg_points*) as a proxy for her long-term past performance.

	Performance Effect	
	Near-term performance	Long-term performance
Intrinsic Utility	+	+
Status Seeking	–	No
Overall	–	+

Table 4. Performance effect

Game effect. We expect a user's expected utility to decrease as the number of games played in a particular session increases. This effect causes a user to stop even if she has had good experience with the game. As the number of game increases, the expected marginal gain in status also decreases. This is because status seeking process is like a repeated sampling process. If one doesn't get a good score after a large number of tries, she probably will not get it the next time. In summary, we expect that the number of games in a session has a negative effect on the probably of continuing.

Session effect. A user's interests in playing the game may increase (if she gets addicted) or decline (if she gets bored with the game) in the number of sessions. In our case, we expect the expect utility to decline in the number of sessions. One reason is the cumbersome design of the SMS-based Mobile Millionaire. Another reason is that there is not much variation in the game to keep users' experience fresh. We expect the status seeking to have no strong long-term effect. We hypothesize that the number of sessions has a negative impact on the probability of continuing.

	Effect of time on continue	
	Game effect	Session effect
Intrinsic Utility	–	–
Status Seeking	–	No
Overall	–	–

Table 5. Effect of time on *continue*

Heterogeneity users. We consider the heterogeneity of users in two dimensions. One dimension is that the general tendency to play such games varies among users. To capture such variation, we differentiate users who played just one session (*trial group*) during the 7 month period and who played multiple sessions (*regular group*). We use a dummy variable (*singletry*) to separate two groups. We expect the trial group to have a lower tendency to continue. Another dimension is that users may play games at different frequencies. We use the total number of games played over the 7 month (*total_games*) period to accommodate such difference. We expect the coefficient of *total_games* to be positive.

Other control variables. We introduce a group of dummy variables (*week_of_year*) to remove time-based variations in the dataset, such as caused by a promotion event. There are total of 31 weeks recorded in our dataset. We include a class variable *end-reason* (which takes 5 values: CA-Correct Answer, WA-Wrong Answer, GE-Game Ends, TO-Time Out, WAW-Walk Away, NA-Unknown) to remove any effect caused by different ending mode. We include the interval before the game (*interval-before*) in case it has any impact on the dependent variable. Finally, we notice that the behavior pattern is different if a user gets zero point in a game than gets positive points, so we add a dummy variable (*zeropoints*) to capture such effect. The following table provides descriptive statistics for the variables.

Variable	Mean	Std Dev	Min	Max
Continue	0.442027	0.496630	0	1
score	0.768795	0.928269	0	4
zeropoints	0.519212	0.499633	0	1
singletry	0.514791	0.499784	0	1
total_games	11.75594	37.12035	1	361
avg_points	1.397252	1.77071	0	14
session_nbr	2.819518	7.682293	1	137
game_within_session	1.738619	1.859093	1	63
interval_before (seconds)	12083.85	21961.57	0	300493

Table 6. Descriptive Statistics

3.4 Results

Our model was estimated using the Probit procedure in SAS 8.0. Table 7 reports the regression results. The likelihood ratio is 22278.7653 (with a degree of freedom 42), indicating an overall model fit. The regression confirmed our hypothesis about the near-term effect. The score of the current game has a strong positive effect on the probability of stop. This implies a strong status-seeking motive among the users – that one wouldn't be satisfied with a low score. A positive coefficient also implies that once a user gets a high score, she tends to stop. Such a behavior is not explained by intrinsic utility argument. We also notice that *zeropoints* has a very strong positive effect on probability of continuing, which also suggest the existence of status seeking motive.

Average past performance in a relative long term has a sizable positive effect on probability of continuing. This implies a user with a good overall experience with the game tends to playing more games in a session.

Our result confirms a negative session effect (*session_nbr*). However, the result rejects a negative game effect (*game_within_session*). One possible explanation is the selection effect: as *game_with_session* increases, the user is more likely to have higher tendency to play. The effect of *Interval_before* is not significantly different from zero. This suggests the game interval does not build up or reduce users' tendency to play longer.

Regressors	DOF	Estimation	Std Err	Pr>ChiSq
Intercept**	1	-1.3634	0.0849	<.0001
Zeropoints**	1	1.4644	0.0373	<.0001
Singletry**	1	-0.294	0.0168	<.0001
Total_games**	1	0.0184	0.0006	<.0001
Score**	1	-0.5299	0.0226	<.0001
avg_points**	1	0.1416	0.0091	<.0001
Session_nbr**	1	-0.0444	0.002	<.0001
Game_within_session**	1	0.0438	0.0071	<.0001
interval_before**	1	0	0	<.0001
end_reason CA**	1	0.4409	0.1434	0.0021
end_reason GE	1	0.4514	0.1948	0.0205
end_reason NA**	1	0.2155	0.0573	0.0002
end_reason TO**	1	0.4268	0.0704	<.0001
end_reason WA**	1	0.6432	0.0519	<.0001
end_reason WAW	0	0	0	.

Table 7. Regression results

We have omitted the regression results for *week_of_year* dummies since there are 30 of them. But we do see a significant positive effect in some weeks (e.g. week 16, 17, 18, and 19). That probably means the promotion campaign was taking effects among these weeks.

3.5 Discussion and Future Research

The main finding of this regression is that while intrinsic utility of playing the game has a positive effect on playing in the long term, in the short term status seeking is the noticable driving force of game play. Because of status seeking, a user tends to continuing playing while their performance is poor and to stop playing when their performance is satisfying.

We did not find long-term status seeking effect in this dataset. This suggests that the game company should work on inducing status seeking across session. The main issue may lie in the use of the highest performance as a way to rank a player. If the game designer could choose a performance measure that can adjust more frequently to game-to-game play, users may come back more often.

This empirical work can be enhanced in a few ways. First of all, a consideration of heterogeneity in status seeking behavior is desirable. Especially, we are interested in how status seeking changes with users' characteristics and with time. Second, the logistic regression can be compared with other possible models, such as a Beta-Binomial model and the conversion model proposed by Moe and Fader (2004).

Appendix

A1 Order Statistics and Its Properties

Let $M_1, M_2, ..., M_n$ be n random variables independently drawn from the common distribution $F(\cdot)$. The corresponding order statistics are M_i 's arranged in non-decreasing order. The smallest of the $M_i's$ is denoted as $M_{1:n}$, the second smallest is denoted by $M_{2:n}$, and so on. Thus $M_{1:n} \le M_{2:n} \le ... \le M_{n:n}$. Denote $F_{1:n}(\cdot), F_{2:n}(\cdot), ..., F_{n:n}(\cdot)$ as their cumulative distribution functions. We also define $F_{0:n}(\mu) \equiv 1$ and $F_{n+1:n}(\mu) \equiv 0$. It is well known that

$$\begin{aligned} F_{j:n}(\mu) &= \sum_{i=j}^{n} \binom{n}{i} F(\mu)^i (1 - F(\mu))^{n-i} \\ &= \int_0^{F(\mu)} \frac{n!}{(j-1)!(n-j)!} x^{i-1} (1-x)^{n-i} dx, \text{ for } 1 \le j \le n. \end{aligned} \tag{16}$$

We define $\omega_{j:n}(\mu) = \frac{1}{j} F_{n-j:n-1}(\mu)$ and use $\omega_j(\mu)$ as a short-hand for $\omega_{j:n}(\sigma)$. In our paper, $\omega_j(\mu)$ represents the equilibrium (expected) share of prize differential j of a user whose skill is μ.

Based on (16), we can derive the formula to be used in this paper.

$$\omega_j(\mu) = \frac{1}{j}\sum_{i=n-j}^{n-1}\binom{n-1}{i}F(\mu)^i(1-F(\mu))^{n-i-1}$$
$$= \int_0^{F(\mu)}\frac{(n-1)!}{(n-j-1)!(j-1)!}x^{n-j-1}(1-x)^{j-1}dx, \text{ for } 1 \le j \le n. \qquad (17)$$

$$\omega'_j(\mu) = \binom{n-1}{n-j-1}F(\mu)^{n-j-1}(1-F(\mu))^{j-1}f(\mu), 1 \le j \le n-1 \quad (18)$$

$$\omega_j(\mu) = 0,\ j = 0 \,\&\, n \qquad (19)$$

$$\int_{\underline{\mu}}^{\bar{\mu}}\omega_j(\mu)f(\mu)d\mu = \frac{1}{n}. \qquad (20)$$

To see the last formula,

$$\int_{\underline{\mu}}^{\bar{\mu}}\omega_j(\mu)f(\mu)d\mu = \frac{1}{j}\sum_{i=n-j}^{n-1}\int_{\underline{\mu}}^{\bar{\mu}}\binom{n-1}{i}F(\mu)^i(1-F(\mu))^{n-i-1}f(\mu)d\mu$$
$$= \frac{1}{j}\sum_{i=n-j}^{n-1}\int_0^1\binom{n-1}{i}x^i(1-x)^{n-i-1}dx,$$

whereas

$$\int_0^1\binom{n-1}{i}x^i(1-x)^{n-i-1}dx = \frac{(n-1)!}{i!(n-i-1)!}\int_0^1(1-x)^{n-i-1}\frac{1}{i+1}dx^{i+1}$$
$$= \int_0^1\binom{n-1}{i+1}x^{i+1}(1-x)^{n-i-2}dx = \ldots = \int_0^1\binom{n-1}{n-1}x^{n-1}dx = \frac{1}{n}.$$

A2 Single Crossing Property

Definition (**single crossing property**). A function $f(x)$ is ***single-crossing*** on $[a,b]$ if $f(x) \ge 0 \Rightarrow f(y) \ge 0, \forall y > x$ and $x, y \in [a,b]$.

Lemma A1: $f(x), g(x)$ *are continuous functions defined on* $[a,b]$. *Assume* $\int_a^b f(x)dx = 0$ *and* $f(x)$ *is single-crossing.* $\int_a^b f(x)g(x)dx \geq 0$ *if either of the following conditions is satisfied.*

(a) $g'(x) \geq 0$ *on* $[a,b]$.

(b) $g'(x) \geq 0$ *on* $[\chi, b]$, $g(x) \leq g(\chi)$ *on* $[a, \chi]$, *and* $f(\chi) \leq 0$.

Proof:

According to the single-crossing property, there exists ξ on $[a,b]$ such that $f(x) \leq 0$, for $x \leq \xi$ and $f(x) \geq 0$, for $x > \xi$.

(a). $\int_a^b f(x)g(x)dx = \int_a^\xi f(x)g(x)dx + \int_\xi^b f(x)g(x)dx$

$\geq g(\xi)\int_a^\xi f(x)dx + g(\xi)\int_\xi^b f(x)dx = g(\xi)\int_a^b f(x)dx = 0$

(b). $\int_a^b f(x)g(x)dx = \int_a^\chi f(x)g(x)dx + \int_\chi^b f(x)g(x)dx$

$\geq g(\chi)\int_a^\chi f(x)dx + g(\xi)\int_\chi^b f(x)dx$

$\geq g(\xi)\int_a^\chi f(x)dx + g(\xi)\int_\chi^b f(x)dx$

$= g(\xi)\int_a^b f(x)dx = 0$.

Lemma A2: *(a) If* $i < j$, $\omega_i(\mu) - \omega_j(\mu)$ *is single-crossing on* $(\underline{\mu}, \overline{\mu})$.

(b) if $n' > n$, $n'\omega_{j:n'}(\mu) - n\omega_{j:n}(\mu)$ *is single-crossing on* $(\underline{\mu}, \overline{\mu})$.

Proof: According to (17),

$$\omega_i(\mu)-\omega_j(\mu)$$
$$=\int_0^{F(\mu)}\frac{(n-1)!}{(i-1)!(n-i-1)!}x^{i-1}(1-x)^{n-i-1}\left[1-\frac{(i-1)!(n-i-1)!}{(j-1)!(n-j-1)!}\left(\frac{x}{1-x}\right)^{j-i}\right]dx$$

Note that the term in square brackets monotonically increases in x. For any a such that $\omega_i(a)-\omega_j(a)>0$, it must be that the term in squire brackets is positive for $x=F(a)$. Since the integrand is positive on $\lfloor a,\overline{\mu}\rfloor$, the entire term is also positive on $\lfloor a,\overline{\mu}\rfloor$. The single-crossing property holds on $(\underline{\mu},\overline{\mu})$ instead of $\lfloor\underline{\mu},\overline{\mu}\rfloor$ because the entire term is zero at two ends.

By the same logic, we can show (b). Just to note that

$$n'\omega_{j:n'}(\mu)-n\omega_{j:n}(\mu)$$
$$=\int_0^{F(\mu)}\frac{(n'-1)!}{(i-1)!(n'-i-1)!}x^{n'-i-1}(1-x)^{i-1}\left[1-\frac{(n-1)!(n'-i-1)!}{(n'-1)!(n-i-1)!}x^{n'-n}\right]dx.$$

A3 Proof of Proposition 1

(Step 1) Let $x(\mu)$ denote the equilibrium performance and assume $x(\mu)$ is strictly increasing (we will check this is indeed true in step 2). Let $U(\mu,x)$ denote the expected utility when a user's skill is μ and she chooses performance x. A user's probability of winning prize j is equal to the probability that her performance falls between $(n-j)$th lowest and $(n-j+1)$th lowest performance of the rest $n-1$ users. It is also equivalent to her skill level (if she also plays according to $x(\mu)$) falls between $(n-j)$th lowest skill level and $(n-j+1)$th lowest skill level of the rest $n-1$ skill levels, i.e.

$$F_{n-j\,:\,n-1}\left(x^{-1}(x)\right)-F_{n-j+1\,:\,n-1}\left(x^{-1}(x)\right)$$

where $x^{-1}(\cdot)$ is the inverse of $x(\cdot)$. Her expected utility (let $v_{n+1}=0$)

$$\begin{aligned}U(\mu,x)&=\sum_{j=1}^{n}v_j\left[F_{n-j\,:\,n-1}\left(x^{-1}(x)\right)-F_{n-j+1\,:\,n-1}\left(x^{-1}(x)\right)\right]-(p-\theta)\frac{Q^{-1}(x)}{\mu}\\&=\sum_{j=1}^{n}\left(v_j-v_{j+1}\right)F_{n-j\,:\,n-1}\left(x^{-1}(x)\right)-(p-\theta)\frac{Q^{-1}(x)}{\mu}\end{aligned}$$

By our notation $\delta_j=j\left(v_j-v_{j+1}\right)$ and $\omega_j(\mu)=\frac{1}{j}F_{n-j:n-1}(\mu)$,

$$U(\mu,x)=\sum_{j=1}^{n}\delta_j\,\omega_j\left(x^{-1}(x)\right)-(p-\theta)\frac{Q^{-1}(x)}{\mu}\qquad(21)$$

Because $x(\mu)$ has to maximize her utility, it is necessary that

$$\frac{\partial U(\mu,x)}{\partial x}=\sum_{j=1}^{n}\delta_j\,\omega_j{}'\left(x^{-1}(x)\right)\frac{dx^{-1}(x)}{dx}-(p-\theta)\frac{\left(Q^{-1}(x)\right)'}{\mu}=0.\ (22)$$

In a symmetric-strategy equilibrium, $x^{-1}(x)=\mu$. Plug into (22) and rearrange terms, we get

$$\sum_{j=1}^{n}\delta_j\,\omega_j{}'(\mu)\,\mu d\mu=(p-\theta)dQ^{-1}(x)$$

The lowest-skilled user always chooses zero performance in equilibrium, so that $x(\underline{\mu})=0$. Using this as a boundary condition, we can solve the above differential equation to obtain an explicit solution,

$$x(\mu)=Q\left(\frac{1}{p-\theta}\sum_{j=1}^{n}\delta_j\int_{\underline{\mu}}^{\mu}\sigma\, d\omega_j(\sigma)\right) \quad (23)$$

It follows that

$$t(\mu)=\frac{1}{p-\theta}\sum_{j=1}^{n}\delta_j\frac{1}{\mu}\int_{\underline{\mu}}^{\mu}\sigma d\omega_j(\sigma).$$

(Part II) Now we verify that (23) is indeed strictly increasing. Note that $Q(\cdot)$ is increasing, so it is sufficient to show that the term in parentheses is increasing. It is true because $\delta_j \geq 0$ (inequality holds for at least one j) and $\int_{\underline{\mu}}^{\mu}\sigma\, d\omega_j(\sigma)\geq 0$ for any μ and any j by (18).

(Part III) We now show that $x(\mu)$ is also sufficient to maximize $U(\mu,x)$. Assume a user with skill μ can choose an arbitrary performance $x'=x(\mu')$. Note that

$$\partial U(\mu,x(\mu'))/\partial\mu'$$
$$=\left[\sum_{j=1}^{n}\delta_j\,\omega_j{}'(\mu')\frac{dx^{-1}(x(\mu'))}{x}-(p-\theta)\frac{(Q(x(\mu')))'}{\mu}\right]x'(\mu')$$

By the first order condition (21), $\partial U(\mu,x(\mu'))/\partial\mu'=0$ at $\mu'=\mu$. Further more, because $Q'(\cdot)>0$ and $x'(\cdot)>0$, $\partial U(\mu,x(\mu'))/\partial\mu'>0$ on $(\mu',\overline{\mu}]$

and $\partial U(\mu, x(\mu'))/\partial\mu' < 0$ on $\lfloor\underline{\mu}, \mu')$. Therefore, $\mu' = \mu$ is a global maximum for $U(\mu, x(\mu'))$. Since this holds for every μ, we conclude that $x(\mu)$ is optimal. The proof process implies it is also unique.

A4 Proof of Proposition 2

As becoming obvious in problem (8), the optimal strategy is to allocate the entire sum to the prize differential with the largest coefficient. Only to note that because $\varepsilon_n = 0$ and $\varepsilon_j > 0$ for any $j < n$, it is never optimal to allocate the prize sum to δ_n. In other words, the company should always keep $v_n = 0$.

A5 Proof of Proposition 3

Exchanging the sequence of integration in (6), followed by integration by parts, we obtain

$$\begin{aligned}\varepsilon_j &= \frac{pn}{p-\theta}\frac{1}{j}\int_{\underline{\mu}}^{\bar{\mu}}\sigma\omega_j{}'(\sigma)\int_{\sigma}^{\bar{\mu}}\frac{1}{\mu}f(\mu)d\mu \\ &= \frac{pn}{p-\theta}\int_{\underline{\mu}}^{\bar{\mu}}\left[\frac{1}{j}\omega_j(\sigma)f(\sigma)\right]\left(1-\frac{\int_{\sigma}^{\bar{\mu}}\frac{1}{\mu}f(\mu)d\mu}{f(\sigma)}\right)d\sigma\end{aligned}$$

Consider the difference between coefficients ε_1 and ε_k.

$$\varepsilon_1 - \varepsilon_k = \frac{pn}{p-\theta}\int_{\underline{\mu}}^{\bar{\mu}}[\omega_1(\sigma) - \omega_k(\sigma)]\, f(\sigma)\left(-\frac{\int_{\underline{\mu}}^{\bar{\mu}}\frac{1}{\mu}f(\mu)d\mu}{f(\sigma)}\right)d\sigma$$

We denote $\eta(\sigma;k,n)=[\omega_1(\sigma)-\omega_k(\sigma)]f(\sigma)$ and $H(\sigma)=-\frac{\int_{\underline{\mu}}^{\overline{\mu}}\frac{1}{\mu}f(\mu)d\mu}{f(\sigma)}$, then the above becomes

$$\varepsilon_1-\varepsilon_k=\frac{pn}{p-\theta}\int_{\underline{\mu}}^{\overline{\mu}}\eta(\sigma;k,n)H(\sigma)d\sigma \quad (24)$$

Notice that $\int_{\underline{\mu}}^{\overline{\mu}}\eta(\sigma;k,n)f(\sigma)d\sigma=0$ by (20) and $\eta(\sigma,k,n)$ is single-crossing by Lemma A2(a). According to Lemma A1(a), a strictly increasing $H(\sigma)$ is sufficient for $\varepsilon_1-\varepsilon_k>0$. Since this holds for every $k\geq 2$, we conclude that ε_1 is the largest if $H(\sigma)$ monotonically increases.

A6 Proof of Proposition 4.

Consider (24). Now we examine an arbitrary $H(\sigma)$. Note that $H(\sigma)$ is continuous and is strictly negative everywhere except $H(\overline{\mu})=0$. Furthermore, conditioning on $f'(\sigma)/f(\sigma)^2$ is bounded $H(\sigma)$ strictly increasing at $\overline{\mu}$ neighborhood. To see this, note that

$$H'(\sigma)=\frac{1}{\sigma}+\frac{f'(\sigma)}{f(\sigma)^2}\int_{\sigma}^{\overline{\mu}}\frac{1}{\mu}dF(\mu)\rightarrow\frac{1}{\sigma}, \text{as } \sigma\rightarrow\overline{\mu}$$

Thus, there must exist $\chi<\overline{\mu}$ such that $H(\sigma)$ strictly increases on $[\chi,\overline{\mu}]$ and $H(\sigma)<H(\chi)$ on $[\sigma,\chi)$. In order to invoke Lemma A2 (b), all we need to show is $\eta(\chi;k,n)<0$. We proceed in two steps.

Claim 1: For any $k \geq 2$, there exists large enough n such that $\eta(\chi;k,n) < 0$.

$$\eta(\chi;k,n) = F(\chi)^{n-1} - \frac{1}{k}\sum_{i=n-k}^{n-1}\binom{n-1}{i}F(\chi)^{i}\left[1-F(\chi)\right]^{n-i-1}$$
$$= F(\chi)^{n-1}\left(\frac{1}{k}\sum_{i=1}^{k}\left[1-\binom{n-1}{i-1}\left(\frac{1-F(\chi)}{F(\chi)}\right)^{i-1}\right]\right)$$
$$< F(\chi)^{n-1}\frac{1}{k}\sum_{i=1}^{k}\left[1-\left(\frac{n-1}{i-1}\frac{1-F(\chi)}{F(\chi)}\right)^{i-1}\right]$$

As $n \to \infty$, $\left(\frac{n-1}{k-i}\frac{1-F(\chi)}{F(\chi)}\right)^{k-i} \to \infty$. So $\eta(\chi;k,n) < 0$ for large enough n.

Claim 2: for large enough k, $\eta(\chi;k,n) < 0$.

$$\eta(\chi;k,n) < F(\chi)^{n-1}\left(1-\frac{1}{k}\sum_{i=1}^{k}\binom{k-1}{i-1}\left(\frac{1-F(\chi)}{F(\chi)}\right)^{i-1}\right)$$
$$= F(\chi)^{n-1}\left[1-\frac{1}{kF(\chi)^{k-1}}\right]$$

As $k \to \infty$, $1-\frac{1}{kF(\chi)^{k-1}} \to -\infty$, so that $\eta(\chi;k,n) < 0$ for large enough k. This holds independent of n (as long as $n \geq k$). Combining the claim 1 and the claim 2, we conclude that $\varepsilon_1 > \varepsilon_k$ when n is large enough.

A7 Proof of the Relationship between Distribution Condition and Hazard-rate Increasing Property

First of all, the hazard-rate-increasing condition is equivalent to

$$\frac{d}{d\sigma}\frac{f(\sigma)}{1-F(\sigma)} = f'(\sigma)(1-F(\sigma)) + f(\sigma)^2 > 0 \quad (25)$$

The Distribution condition $d\left[f(\sigma)/\int_{\sigma}^{\bar{\mu}}\frac{1}{\mu}f(\mu)d\mu\right]/d\sigma > 0$ is equivalent to

$$f'(\sigma)\sigma\int_{\sigma}^{\bar{\mu}}\frac{1}{\mu}f(\mu)d\mu + f(\sigma)^2 \geq 0$$

The above inequality holds naturally for $\{\sigma \mid f'(\sigma) \geq 0\}$. (25) ensures that it also holds for $\{\sigma \mid f'(\sigma) < 0\}$ because

$$f'(\sigma)\sigma\int_{\sigma}^{\bar{\mu}}\frac{1}{\mu}f(\mu)d\mu + f(\sigma)^2 \geq f'(\sigma)(1-F(\sigma)) + f(\sigma)^2.$$

A8 Proof of Proposition 5

Denote π_n as the company's expected profit from a SBCC of size n.

$$\pi_{n+1} - \pi_n = \frac{p}{p-\theta}\sum_{j=1}^{n-1}\delta_j\int_{\underline{\mu}}^{\bar{\mu}}\left[(n+1)\omega_{j:n+1}(\sigma) - n\omega_{j:n}(\sigma)\right]f(\sigma)H(\sigma)d\sigma$$

Note that $\int_{\underline{\mu}}^{\bar{\mu}}\left[(n+1)\omega_{j:n+1}(\sigma) - n\omega_{j:n}(\sigma)\right]f(\sigma)d\sigma = 0$ and $(n+1)\omega_{j:n+1}(\sigma) - n\omega_{j:n}(\sigma)$ is single-crossing by Lemma A2 (b). Apply Lemma A1(a), a strictly increasing $H(\sigma)$ is sufficient for $\pi_{n+1} - \pi_n > 0$. Similar to the proof of Proposition 4, we can show that $\pi_{n+1} - \pi_n > 0$ also holds for sufficiently large n.

The following obtains an upper bound for the company's profit.

$$\pi_n = \frac{pn}{p-\theta}\sum_{j=1}^{n-1}\delta_j \int_{\underline{\mu}}^{\bar{\mu}} \omega_j(\sigma)\left[1-\frac{\int_{\sigma}^{\bar{\mu}}\frac{1}{\mu}f(\mu)d\mu}{f(\sigma)}\right] f(\sigma)d\sigma$$

$$= \frac{p}{p-\theta}\left(1-n\sum_{j=1}^{n-1}\delta_j \int_{\underline{\mu}}^{\bar{\mu}} \omega_j(\sigma)\int_{\sigma}^{\bar{\mu}}\frac{1}{\mu}f(\mu)d\mu d\sigma\right) < \frac{p}{p-\theta}$$

This holds for any distribution, any prize structure, and any n.

A9 Proof of Proposition 6

Let $u = F(\mu)$ and $s = F(\sigma)$, $t_1(u)$ can be re-written as,

$$t_1(u) = \frac{1}{p-\theta}\sum_{j=1}^{n-1}\delta_j \int_0^u \frac{F^{-1}(s)}{F^{-1}(u)}\binom{n-1}{j} s^{n-j-1}(1-s)^{j-1} ds$$

$$t_1(u) - t_2(u) = \frac{1}{p-\theta}\sum_{j=1}^{n-1}\delta_j \int_0^u \left[\frac{G^{-1}(s)}{G^{-1}(u)} - \frac{F^{-1}(s)}{F^{-1}(u)}\right]\binom{n-1}{j} s^{n-j-1}(1-s)^{j-1} ds$$

A sufficient condition for $t_1(u) - t_2(u) > 0$ is

$$\frac{F^{-1}(u)}{F^{-1}(s)} > \frac{G^{-1}(u)}{G^{-1}(s)}, \forall 0 \le s < u \le 1 \qquad (26)$$

Because (26) ensures $t_1(u) > t_2(u)$ for every percentile u, the profit of $\mathbf{C}_1$ will be larger than that of $\mathbf{C}_2$. In fact, it will be so as long as the company's profit is an increasing function of usage.

A10 Proof of Corollary 1

We consider $\mathbf{C}_1$ and an equivalence of $\mathbf{C}_2$, i.e. a contest with the performance $X(\mu,t)$ but skill distribution $G(\cdot)$, where $G(\cdot)$ is defined by $G^{-1}(u)=\phi(F^{-1}(u))$. According to proposition 6, a sufficient condition for $\pi_1 > \pi_2$ is $\frac{\mu}{\sigma} > \frac{\phi(\mu)}{\phi(\sigma)}, \underline{\mu} \le \sigma < \mu \le \overline{\mu}$, which is equivalent to $\frac{\sigma + \Delta\sigma}{\sigma} > \frac{\varphi(\sigma+\Delta\sigma)}{\varphi(\sigma)}, \Delta\sigma > 0$. Let $\Delta\sigma \to 0$, we obtain an alternative sufficient condition for $\pi_1 > \pi_2$, i.e. $\phi'(\sigma)\sigma - \phi(\sigma) < 0$. This condition holds if MRS in $\mathbf{C}_1$ is higher because

$$MRS_1 - MRS_2 > 0 \Rightarrow \frac{\phi(\sigma)}{t\phi'(\sigma)} - \frac{\sigma}{t} > 0 \Rightarrow \phi(\sigma) - \sigma\phi'(\sigma) > 0.$$

A11 Proof of Proposition 7

Let $t_e(\mu)$ denote the new equilibrium consumption. We can derive $t_e(\mu)$ in the same way as in the proof of Proposition 1 except that the boundary condition becomes $x(\mu_e)=0$.

$$t_e(\mu) = \frac{1}{p-\theta}\sum_{j=1}^{n-1}\delta_j \frac{1}{\mu}\int_{\mu_e}^{\mu}\sigma\frac{1}{j}F_{n-j:n-1}{}'(\sigma)d\sigma \quad (27)$$

where μ_e is determined by the condition

$$U(\mu_e,0)=0=\sum_{j=1}^{n-1}\delta_j\frac{1}{j}F_{n-j:n-1}(\sigma)-E\ .(28)$$

The company's total profit is

$$\pi=n\left[p\int_{\mu_e}^{\bar{\mu}}t_e(\mu)f(\mu)d\mu+E\cdot[1-F(\mu_e)]\right].$$

Substitute (27) and (28) in the above expression and focus on the Winner-Take-All prize structure, we can get

$$\pi=n\left[\frac{p}{p-\theta}\int_{\mu_e}^{\bar{\mu}}\frac{1}{j}F_{n-1:n-1}{}'(\sigma)\sigma\int_{\sigma}^{\bar{\mu}}\frac{1}{\mu}f(\mu)d\mu d\sigma+F_{n-1:n-1}(\mu_e)(1-F(\mu_e))\right].$$

Take first order derivative with respect to μ_e, apply $F_{n-1:n-1}(\mu_e)=F(\mu_e)^{n-1}$, and collect items,

$$\frac{\partial\pi}{\partial\mu_e}=n(n-1)F(\mu_e)^{n-2}f(\mu_e)\left[\int_{\mu_e}^{\bar{\mu}}\left(\frac{n}{n-1}-\frac{p\mu_e}{(p-\theta)\mu}\right)f(\mu)d\mu-\frac{1}{n-1}\right].$$

The sign of the derivative is determined by the term in square brackets. Denote this term as $A(\mu_e)$. Note that at $A(\bar{\mu})=-\frac{1}{n-1}$ and $A(\underline{\mu})=1-\frac{p}{p-\theta}\int_{\underline{\mu}}^{\bar{\mu}}\frac{\underline{\mu}}{\mu}f(\mu)d\mu$. If $A(\underline{\mu})>0$, then there must be an interior point μ_e^* such that the total profit reaches its maximum. Thus a sufficient condition for the company to charge a positive entry fee is

$$A(\underline{\mu})=1-\frac{p}{p-\theta}\int_{\underline{\mu}}^{\bar{\mu}}\frac{\underline{\mu}}{\mu}f(\mu)d\mu>0\Rightarrow\frac{p}{p-\theta}<\left[\int_{\underline{\mu}}^{\bar{\mu}}\frac{\underline{\mu}}{\mu}f(\mu)d\mu\right]^{-1}$$

A necessary condition for optimal entry fee is that μ_e^* solves

$$A(\mu_e) = \int_{\mu_e}^{\bar{\mu}} \left(\frac{n}{n-1} - \frac{p\mu_e}{(p-\theta)\mu} \right) f(\mu) d\mu - \frac{1}{n-1} = 0$$

Note also that if $p/(p-\theta)$ is high enough such that $A(\mu)$ is negative throughout the support, the company should optimally charge no entry fee.

A12 Proof of Proposition 9

Notice that with reservation utility,

$$\varepsilon_1 - \varepsilon_k = \frac{pn}{p-\theta} \int_{\mu^0}^{\bar{\mu}} [\omega_1'(\sigma) - \omega_k'(\sigma)] \sigma \int_{\sigma}^{\bar{\mu}} \frac{1}{\mu} f(\mu) d\mu d\sigma$$

By (18), we can easily show that $\omega_1'(\sigma) - \omega_k'(\sigma)$ is single-crossing. Therefore as μ^0 increases but does pass the crossing point, $\varepsilon_1 - \varepsilon_k$ only becomes more positive. Obviously, if μ^0 passes the crossing point, $\varepsilon_1 - \varepsilon_k$ can only be positive. Combining the above two observations, we conclude that the conditions we obtained in A5 and A6 are still valid in this case.

A13 Proof of Proposition 10

Assume the prize structure $(\delta_1, \delta_2, ... \delta_{n-1})$ is optimal. Assume $\delta_k > 0$, by optimality,

$$\left(p-\theta\right)R=\sum_{j=1}^{n-1}\delta_j\omega_j\left(\mu^0\right)\geq\sum_{j=1}^{n-1}\delta_j\omega_j\left(\mu^0\right)+\Delta\left(\omega_j\left(\mu^0\right)-\omega_k\left(\mu^0\right)\right),\text{ for }\Delta<\delta_k .$$

Otherwise, a prize structure $\left(\delta_1,\delta_2,...,\delta_k-\Delta,...,\delta_j+\Delta,...,\delta_{n-1}\right)$ can deliver higher expected utility and therefore attract users (note $\omega_j\left(\mu\right)$ is increasing in μ). So it must be $\omega_k\left(\mu^0\right)\geq\omega_j\left(\mu^0\right)$, for any j. Thus we conclude that the optimal prize structure allocates positive prize sum to the prize differential only if it's on the envelope of $\omega_j\left(\mu\right)$'s.

Assume $u=F\left(\mu\right)$, we can rewrite $\omega_j\left(\mu\right)$ in terms of percentile as

$$\omega_j\left(u\right)=\frac{1}{j}F_{n-j:n-1}\left(F^{-1}\left(u\right)\right)=\int_0^u\frac{\left(n-1\right)!}{j!\left(n-j-1\right)!}x^{j-1}\left(1-x\right)^{n-j}dx .$$

From the above we can see that $\omega_j\left(u\right)$ is independent of $F\left(\cdot\right)$. Because for any distribution, u is uniformly distributed, we conclude that the shape of $\omega_j\left(u\right)$ and $\omega\left(u\right)$ is invariant to the underlying distribution $F\left(\cdot\right)$. This implies that the optimal number of prizes is invariant to the underlying distribution.

By Lemma A2 (a), $\omega_i\left(u\right)-\omega_j\left(u\right), i<j$ is single-crossing. Furthermore, we can also see from the proof of Lemma A2 that the crossing point decreases in j. Combining with the fact that $\omega_j\left(u\right)$ monotonically increases in u, we can infer that $\omega\left(u\right)$ monotonically increases and is connected from low to high by

$\omega_{n-1}(u), \omega_{n-2}(u), \ldots, \omega_1(u)$. Therefore, as R increases, the optimal number of prizes is non-increasing.

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